

1 Typicality in the brain during semantic and episodic memory decisions

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1 **Abstract**

2 Concept typicality is a key semantic dimension supporting the categorical organization of items based
3 on their features, such that typical items share more features with other members of their category than
4 atypical items, which are more distinctive. Typicality effects manifest in better accuracy and faster
5 response times during categorization tasks, but higher performance for atypical items in episodic
6 memory tasks, due to their distinctiveness. At a neural level, typicality has been linked to the anterior
7 temporal lobe (ATL) and the inferior frontal gyrus (IFG) in semantic decision tasks, but patterns of brain
8 activity during episodic memory tasks remain to be understood. We investigated the neural correlates
9 of typicality in semantic and episodic memory to determine the brain regions associated with semantic
10 typicality and uncover effects arising when items are reinstated during retrieval. In an fMRI study, 26
11 healthy young subjects first performed a category verification task on words representing typical and
12 atypical concepts (encoding), and then completed a recognition memory task (retrieval). In line with
13 previous literature, we observed higher accuracy and faster response times for typical items in the
14 category verification task, while atypical items were better recognized in the episodic memory task.
15 During category verification, univariate analyses revealed a greater involvement of the angular gyrus
16 for typical items and the inferior frontal gyrus for atypical items. During the correct recognition of old
17 items, regions belonging to the core recollection network were activated. We then compared the
18 similarity of the representations from encoding to retrieval (ERS) using Representation Similarity
19 Analyses. Results showed that typical items were reinstated more than atypical ones in several regions
20 including the left precuneus and left anterior temporal lobe (ATL). Our findings confirm the centrality
21 of the ATL in the processing of typicality while extending it to memory retrieval. We also demonstrated
22 that the correct retrieval of typical items requires finer-grained processing, evidenced by greater item-
23 specific reinstatement, which is needed to resolve their confusability with other members of the category
24 due to their higher feature similarity.

25

26 **Keywords:** episodic memory, semantic memory, fMRI, typicality

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1 **Introduction**

2 Semantic and episodic memory are two declarative long-term memory systems known to interact very
3 closely (Tulving, 1972, 1985). The former holds our semantic knowledge about the world, abstracted
4 away from our experiences (e.g., the meaning of words) and applied to a variety of contexts. The latter
5 instead refers to episodic events personally experienced in the past, which emerges from the binding of
6 information that co-occurred in the specific context where the event took place. Even though the
7 independence of these two systems is supported by neuroimaging and clinical evidence (Tulving, 1972,
8 1985), they also demonstrate an interplay, such that semantic processing may, for example, enhance
9 episodic retrieval (e.g., levels of processing and semantic congruency effects, Bartlett, 1932; Craik &
10 Lockhart, 1972) or, instead, hinder episodic remembering (e.g., giving rise to false memories; see
11 Greenberg & Verfaellie, 2010 for review). Recent research has questioned the idea of a clear separation
12 between episodic and semantic systems, as they seem to be supported by at least partially overlapping
13 brain networks and common retrieval processes (Greenberg & Verfaellie, 2010; Irish & Vatansever,
14 2020; Renoult et al., 2019).

15 One of the most integrative theoretical accounts of semantic memory, the Hub-and-Spoke model, holds
16 that semantic categories arise from intrinsic regularities among conceptual features of objects.
17 According to this model, the anterior temporal lobe (ATL), which includes the temporal gyri, temporal
18 pole, rhinal cortices, fusiform and parahippocampal gyri (Bonner & Price, 2013), works as a semantic
19 hub, which amodally integrates conceptual information and forms abstractions or generalizations across
20 categories (Patterson et al., 2007; Ralph Lambon et al., 2017). Yet, it remains unclear how the natural
21 variability in the conceptual features of items of the same category is represented by the human brain,
22 with some authors relating it to their typicality (Santi et al., 2016; Woollams, 2012; Woollams et al.,
23 2008). Indeed, a key property of concepts is their graded category membership, according to which some
24 members are more typical, or a better exemplar of the category than others (Rosch & Mervis, 1975).
25 Within a given category (e.g., bird), a typical item (e.g., sparrow) shares many features with the other
26 members of its category while, conversely, an atypical item (e.g., penguin) is characterized by more
27 idiosyncratic features, making atypical items more distinctive within their category. Hence, according
28 to some authors, typicality reflects the conceptual structure as expressed by the co-occurrence of features
29 between concepts within a given category (Raposo et al., 2012).

30 Behaviorally, typical items are systematically associated with faster response times and lower error rates
31 than atypical items in naming (Holmes & Ellis, 2006) and category verification tasks (Kiran et al., 2007).
32 However, at a neural level, results are more inconsistent, which may be partly due to the different tasks
33 used (i.e., naming, categorization, feature verification) or the stimuli adopted (words vs. pictures; e.g.,
34 see Davis & Poldrack, 2014; Jordan et al., 2016; Li et al., 2021). On one hand, studies on patients with
35 semantic dementia (SD), presenting with ATL atrophy (Woollams et al., 2008), and with healthy

1 controls following Transcranial Magnetic Simulation (TMS) on the ATL (Woollams, 2012), showed
2 that disruption of the ATL leads to impairments in naming tasks for more atypical concepts, and an
3 fMRI study with healthy participants showed increased activation in the ATL with decreasing item
4 typicality during a category verification task (Santi et al., 2016). On the other hand, studies using
5 Representational Similarity Analysis (RSA, Kriegeskorte et al., 2008) have shown that, in the ATL
6 region, the semantic similarity between concepts (as measured by feature norms, indexing their shared
7 and distinctive features) matches similarity between voxel patterns elicited by objects processed
8 semantically (Borghesani et al., 2016; Bruffaerts et al., 2013; Chen et al., 2016; Clarke, 2020; Clarke &
9 Tyler, 2014; Fairhall & Caramazza, 2013; Liuzzi et al., 2015; Martin et al., 2018). Taken together, these
10 results support the idea that concepts are processed and represented in the ATL as unique complex
11 entities according to the integration of their constituting features, both shared and distinctive ones
12 (Bruett et al., 2020; Bruffaerts et al., 2019; Coutanche & Thompson-Schill, 2015).

13 Beyond the ATL, researchers have identified a supramodal left-lateralized network, comprising the
14 posterior middle/inferior temporal gyrus, angular gyrus (AG), ventral temporal cortex, precuneus (PC),
15 and lateral and dorsomedial prefrontal cortex, representing semantic content during a typicality
16 judgement task (Fairhall & Caramazza, 2013). In addition, imaging work on semantic categorization of
17 items varying in typicality has revealed increased activation in the inferior frontal gyrus (IFG) for more
18 atypical items, whereas typical items displayed enhanced activation in the inferior parietal and posterior
19 temporal regions (Santi et al., 2016). These findings are corroborated by a recent fMRI study
20 demonstrating that, in addition to the ATL, the left IFG was significantly more recruited during the
21 processing of distinctive (e.g., has a mane) than shared features (e.g., has four legs) of concepts, whereas
22 the right AG revealed the opposite pattern (Reilly et al., 2019). Together, these results suggest that
23 processing atypical items, which possess more distinctive features, requires greater semantic control
24 possibly due to the lower feature co-occurrence (Santi et al., 2016). Conversely, inferior parietal regions,
25 including the AG, are engaged in similarity-based categorization (Grossman et al., 2002), and possibly
26 function as another cross-modal semantic hub, integrating semantic features within a single concept or
27 across concepts for integration with broader memory and cognitive processes (Bonner et al., 2013;
28 Bonnici et al., 2016; Farahibozorg et al., 2022; Seghier, 2013).

29 Understanding how the organization of semantic memory influences episodic memory mechanisms
30 remains of key concern, especially considering that little is yet known about the role that typicality plays
31 in it. Only a few studies have explored this issue and they consistently showed that atypical items are
32 associated with better recognition memory than typical ones, and this difference may be attributed to
33 increased recollection rather than familiarity (Alves & Raposo, 2015; Souza et al., 2021). One
34 interpretation of this effect is that atypical items are more distinctive, because of their idiosyncratic
35 features compared to other members of their category (e.g., a penguin among typical birds; Hunt, 2013;
36 Tulving & Rosenbaum, 2006), which may have beneficial effects on episodic memory encoding

1 (von Restorff, 1933). The impact of typicality on subsequent memory has also been studied in the
2 context of expectancies, or predictions. In the presence of a category-cue, expectations would build up
3 towards typical items, while atypical items, that are unexpected, elicit a mismatch between the presented
4 stimulus and the prediction (Federmeier et al., 2010). Such mismatch detection can benefit subsequent
5 memory (Federmeier et al., 2007; but see Hölzje et al., 2019).

6 Whether concept typicality affects the neural correlates of successful memory retrieval has never been
7 explored. To address this question, we used fMRI in both a semantic categorization task during encoding
8 of typical and atypical items and a subsequent recognition memory task. We first conducted contrast
9 analysis to inspect the effects of typicality on the neural bases of semantic category verification. We
10 anticipated that the categorization of atypical items should be associated with greater ATL and IFG
11 activation, while for typical items, we expected greater engagement of the right inferior parietal lobe
12 including the AG (Reilly et al., 2019; Santi et al., 2016; Woollams et al., 2012). Next, we explored if
13 typicality impacts concept recognition, by contrasting old vs. new items that were typical or atypical
14 members of the category. In complement, we conducted RSA to test if the neural patterns of semantic
15 processing at encoding were reinstated differently for typical and atypical items during retrieval, both at
16 the whole-brain level, and using Region of Interest (ROI) analysis focusing on the ATL. One hypothesis
17 is that atypical concepts (relative to typical ones) will reveal higher similarity from encoding to retrieval
18 due to their greater distinctiveness and results in greater item-unique effects. Alternatively, since typical
19 concepts are more similar to other members of the category and hence more confusable, their correct
20 retrieval may involve fine-grained processing, which could instead lead to greater item-specific
21 reinstatement, which we expect to occur in the left ATL.

22 23 **Methods**

24 *Participants*

25 26 young healthy adults took part in this fMRI study (20 females, $M=21.46$ years old ($SD=3.57$),
26 range=18-29). All subjects were right-handed, native speakers of Portuguese, and had no history of
27 neurological impairment or head injury. Participants took part in the study in exchange for course
28 credits. They all gave informed written consent to the experimental procedure, which was approved by
29 the ethics committee of Faculdade de Psicologia, Universidade de Lisboa.

30 *Materials and Procedure*

31 We selected 160 words from 10 categories, so to have 16 items per category (fruit, vegetable, bird,
32 insect, mammal, vehicle, musical instrument, clothing, weapon, kitchen utensil). Half of the words
33 consisted of typical members of their category, while the other half were atypical members of their
34 category. Typicality was determined in a previous pretest (see Santi et al., 2016) in an independent group

1 of participants who judged how typical an exemplar is for a given category on a 7-point scale (1=very
2 atypical to 7=very typical).

3 During encoding, participants saw 80 words (40 typical and 40 atypical) for which they were instructed
4 to perform a category verification task. Half of the words were presented with the actual category they
5 belong to, so that they were part of a “congruent” condition (20 typical, 20 atypical), while the other
6 half were presented with an incongruent category (20 typical, 20 atypical). So, our design included 4
7 conditions: congruent typical, congruent atypical, incongruent typical and incongruent atypical. Items
8 in the typical and atypical conditions differed in terms of typicality ratings ($t(17.19)=42.92, p<.001$).
9 All conditions were matched in familiarity (all $ps>.30$) and the number of letters (all $ps > .29$; see Table
10 1). Each trial began with the presentation of a fixation cross for 500 ms followed by the category cue
11 (prime) for 750 ms. The prime was followed by a 200 ms blank screen, and the target concept was then
12 presented for 2000 ms, during which participants had to perform the category verification task, by
13 pressing the left index finger for “yes” and the left middle finger for “no”. The target was followed by
14 a jittered 1500-3000 ms blank screen, ending the trial (see Figure 1).

15 During retrieval, participants were presented with the 80 words they saw during encoding, and an
16 additional 80 new words, half of which were typical members of their category, and the other half,
17 atypical members. New words were matched with the old words in terms of the category they belong
18 to, typicality ratings, familiarity ratings and number of words ($ps >.1$ in all cases; see Table 1).
19 Participants were asked to determine whether they saw the item previously in a yes-no recognition task
20 by pressing the same keys as during encoding, and then to judge the confidence of their answer on a 4-
21 point scale (using the left hand). Each trial started with a fixation cross presented for 500 ms followed
22 by the probe (target concept) for 2500 ms, during which participants had to determine whether the item
23 was old or new. The probe was followed by a 200 ms blank screen, after which the screen displayed the
24 confidence judgement scale for 2000 ms during which participants were asked to provide their
25 confidence judgement. The trial ended with a jittered 2000-3500 ms blank screen. The order of
26 presentation of the words was randomized across participants. Both the category verification task and
27 the recognition phases were performed in the scanner. See Figure 1 for an example of the design of the
28 tasks.

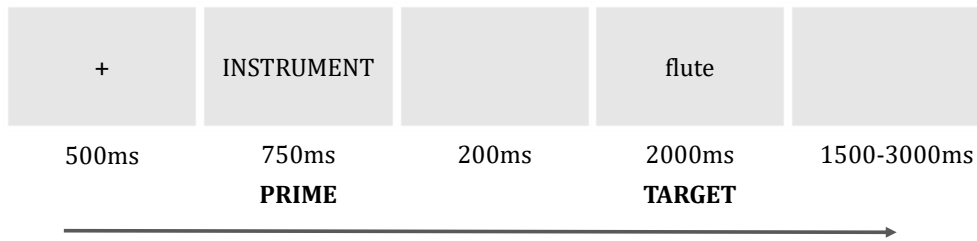
Table 1. Descriptive statistics (mean, and SD in brackets) of the stimuli characteristics

		Number of letters	Familiarity (1-7)	Typicality (1-7)
Typical	Congruent	6.65 (2.28)	4.20 (1.03)	6.68 (0.20)
	Incongruent	6.10 (2.07)	4.16 (1.41)	6.70 (0.22)
	New	6.42 (1.65)	4.02 (1.07)	6.54 (0.30)
Atypical	Congruent	6.45 (1.96)	3.93 (0.96)	4.08 (0.93)
	Incongruent	7.00 (2.90)	4.46 (1.15)	4.10 (0.96)
	New	7.02 (3.47)	4.33 (1.17)	4.12 (1.08)

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Encoding (scanned) – category verification task



Retrieval (scanned) – old/new recognition memory task



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Figure 1. Experimental task. Top: category verification task for typical and atypical items, bottom: recognition memory task where old congruent items from the category verification task were interspersed among new typical and atypical items from the same categories

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MRI data acquisition and preprocessing

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Scanning was conducted at Sociedade Portuguesa de Ressonância Magnética on a 3T Philips MR system (Philips Medical Systems, Best, NL) using a standard head coil. Functional data were acquired by using an echo-planar sequence (TR=2000ms, TE=23ms, FA=90°, FOV=230×230 mm, 34 bottom-up interleaved slices parallel to the AC-PC line, with 1.8 x 1.8 x 3.5 mm voxels size, matrix size=116x115). Acquisition covered the entire brain. Before functional data collection, three dummy volumes were discarded to allow for T1 equilibrium. High-resolution T1-weighted anatomical images were acquired for visualization and spatial processing of the fMRI (coregistration and normalisation).

1 The fMRI data were preprocessed and statistically analyzed using Statistical Parametric Mapping
2 toolbox (SPM12, Wellcome Institute of Cognitive Neurology, www.fil.ion.ucl.ac.uk) within Matlab
3 (version 2015b, Mathworks Mathworks Inc., Sherborn MA, USA). First, we corrected for differences
4 in slice acquisition timing by resampling all slices to the middle slice. These data were then corrected
5 for motion across all sessions by aligning to the mean of the images collected after the first realignment.
6 The mean resliced functional data were coregistered to the participants' T1. The T1 was then segmented
7 in order to obtain the normalization parameters. Voxel size was resampled into isotropic 2 x 2 x 2 mm.
8 The normalization parameters were then applied to the preprocessed functionals. Normalized functional
9 data were then spatially smoothed with an isotropic Gaussian kernel of 8 mm FWHM.

10 *Behavioral data analyses*

11 Data from the encoding category verification task were analyzed using a repeated-measures ANOVA
12 with congruency (congruent, incongruent) and typicality (typical, atypical) as within-subject variables
13 on the proportion of correct answers and on the response time for correct trials. As for the recognition
14 task, we ran repeated measures ANOVAs on the hit rates, hits with high confidence responses only
15 (level 4), false alarm rates (FAs), and hits-FAs global accuracy measure. The repeated measures
16 ANOVAs on the hit rates and the hits-FAs accuracy measure included congruency between the target
17 and the prime during the encoding category-verification task (congruent, incongruent) as well as
18 typicality (typical, atypical) as within-subject factors. The repeated-measures ANOVA on the FAs
19 included typicality (typical, atypical) as the within-subject factor.

20 *fMRI data analyses*

21 *Univariate analyses*

22 For each participant, BOLD responses were modelled using the General Linear Model (GLM)
23 implemented in SPM12. In the category verification task, regressors of interest were modelled as epochs
24 that began when the prime (category cue) was presented and finished before the onset of the next prime
25 (4.95-6.45 sec). The design matrix included 4 regressors: typical targets that were congruent with the
26 prime, atypical targets that were congruent with the prime, typical targets that were incongruent with
27 the prime, atypical targets that were incongruent with the prime.

28 The analysis of the recognition memory task focused on trials associated with a correct response (i.e.,
29 accurate recognition) as several studies have reported neural differences as a function of retrieval success
30 (e.g., Herron et al., 2004). Regressors of interest were modelled as epochs that began with the onset of
31 the probe and finished before the onset of the next probe (7.2-8.7 sec). The design matrix included 6
32 regressors: old items from the congruent typical condition, old items from the congruent atypical
33 condition, new typical items, new atypical items, old items from the incongruent condition and incorrect
34 responses. We included only one regressor for all incongruent trials as this condition led to relatively

1 low levels of recognition accuracy (incongruent typical: $M=.56$, $SD=0.18$; incongruent atypical: $M=.64$,
2 $SD=0.17$), with lower confidence in producing correct responses (see Behavioral results section). Hence,
3 there were not enough correct trials to conduct further analyses on these items. Each design matrix
4 included realignment as nuisance parameters to model movement-related variance.

5 At the individual subject level (first level), we generated a contrast for each condition of interest versus
6 rest, used as a baseline. The contrast images were then submitted to a second-level analysis
7 corresponding to a random effects model in which subjects were considered as random variables, using
8 factorial ANOVAs in SPM12, and follow-up pairwise comparisons between conditions were
9 implemented using two-sample t -tests. Data from the category verification task were analyzed in a
10 factorial ANOVA, with congruency (congruent, incongruent) and typicality (typical, atypical) as factors.
11 As for the recognition task, we conducted a factorial ANOVA, with probe status (old, new) and
12 typicality (typical, atypical) as factors.

13 The significance voxel-level threshold was set at $p<.001$, uncorrected, and the cluster-level threshold of
14 78 contiguous (resampled) voxels (k), to correct for multiple comparisons, at $p<.05$, as determined by
15 Monte Carlo simulations (N iterations 10 000) using the current study's imaging and analysis parameters
16 as recommended by Slotnick et al. (2003).

17 *Multivariate analyses*

18 RSA was used to examine the neural similarity of typical and atypical items from encoding to retrieval
19 (Encoding-Retrieval Similarity, ERS) across participants (Kriegeskorte et al., 2008). The unsmoothed
20 preprocessed fMRI images were used for these analyses. A beta value was generated for each trial of
21 encoding and retrieval. Trials were modelled as 0 s-duration events (see Folville et al., 2020; Wing et
22 al., 2015, for a similar approach), along with regressors corresponding to realignment as nuisance
23 parameters to model movement-related variance. The CoSMoMVPA toolbox (Oosterhof et al., 2016)
24 was then used to perform RSA analyses using the resulting betas. To examine neural similarity across
25 participants, a searchlight procedure was used (Kriegeskorte et al., 2008).

26 For each trial, we computed ERS at the item level (corresponding to the similarity of patterns of brain
27 activity between the encoding and retrieval of a given item) and the set level (i.e., the comparison of the
28 patterns of brain activity associated with the retrieval of a given item with patterns of brain activity
29 associated with the encoding of the remaining items from the same condition – typical or atypical). The
30 set level measures the general reactivation of concept processing, while the item level measures the
31 specific reactivation of a given concept. Thus, any difference observed between the item and the set
32 levels indicates that cognitive processes specific to a given concept were reactivated during retrieval
33 (see Figure 8D for an illustration of the ERS matrix).

1 For both the item and set levels, we applied a searchlight to the betas (Kriegeskorte et al., 2008) with a
2 vectorized 3 x 3 x 3 voxel cube, and Fisher-Transformed Pearson correlations were used to measure
3 ERS. In the item level ERS analysis, the correlation was computed between encoding and retrieval for
4 each item (e.g., flute x flute). In the set-level ERS analysis, for a given item, the retrieval of this item
5 was correlated with the encoding of the remaining items (e.g., flute x piano, flute x sparrow, flute x coat,
6 etc.) and the correlations were averaged. Thus, for each item and each voxel, we obtained a correlation
7 value for the item and the set level. Then, in SPM12, we conducted a 2 typicality (typical, atypical) by
8 2 levels (item, set) factorial ANOVA on ERS maps. Following the same criteria of the univariate
9 analysis, we restricted the analysis to items that were presented with a congruent category cue during
10 learning and accurately recognized at test (mean number of trials, typical=15.61, atypical=17.22). We
11 used a cluster-defining threshold of $p < .001$ with clusters significant at $p < .05$ (FWE cluster corrected)
12 (Bird et al., 2015; Oedekoven et al., 2017).

13 In addition to the whole brain ERS analysis, we ran a supplementary ROI analysis that focused
14 specifically on the left ATL since, as discussed at the outset, the ATL is a core region in processing item
15 typicality and is known to be susceptible to signal distortion and signal loss in fMRI because of its
16 position near the sinuses (Olman et al., 2009; Visser et al., 2010). For that, we used the Marsbar toolbox
17 in SPM (Brett et al., 2002), and defined a 10mm-radius sphere around coordinates reported in a previous
18 independent study assessing ERS using an ATL ROI at -41, 8, -17 (Bruett et al., 2020; see also
19 Coutanche & Thompson-Schill, 2015). The same 2 typicality (typical, atypical) by 2 levels (item, set)
20 factorial ANOVA was run on ERS maps within this ROI.

21 **Results**

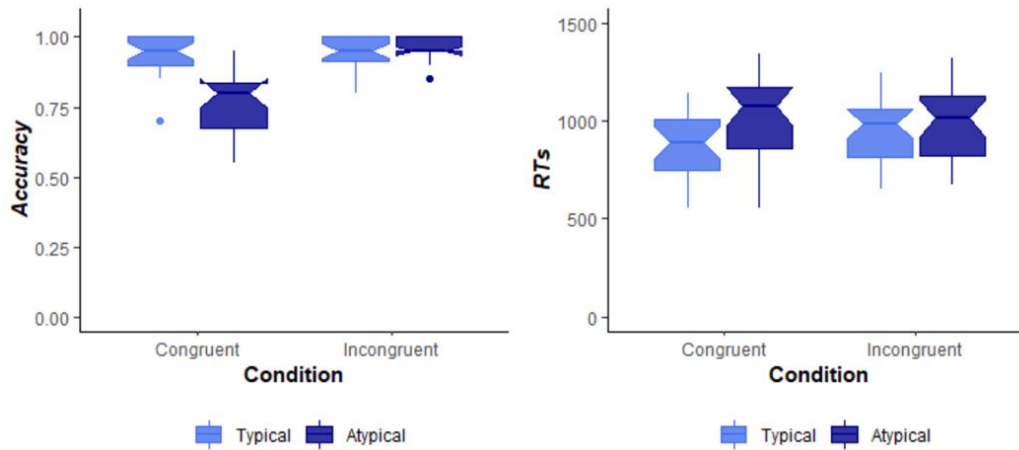
22 ***Behavioral results***

23 *Category verification task*

24 The repeated measures ANOVA on the proportion of correct answers with congruency (congruent,
25 incongruent) and typicality (typical, atypical) as within-subject factors was characterized by a main
26 effect of congruency, $F(1,25)=31.79$, $p < .001$, $\eta^2_p=.56$, with better performance for incongruent than
27 congruent targets. There was also a main effect of typicality, $F(1,25)=43.76$, $p < .001$, $\eta^2_p=.64$, with more
28 accurate categorization of typical than atypical items. The congruency x typicality interaction was also
29 significant, $F(1,25)=64.43$, $p < .001$, $\eta^2_p=.72$, according to which, for the incongruent condition, there
30 was no difference in categorization accuracy between typical and atypical items ($p=1.00$, Bonferroni
31 post-hoc test), while in the congruent condition, categorization was significantly better for the typical
32 than atypical items ($p < .001$) (see Figure 2).

33 Regarding response times, we found a main effect of typicality, $F(1,25)=57.29$, $p < .001$, $\eta^2_p=.68$, with
34 typical items leading to faster responses than atypical items. There was no main effect of congruency,

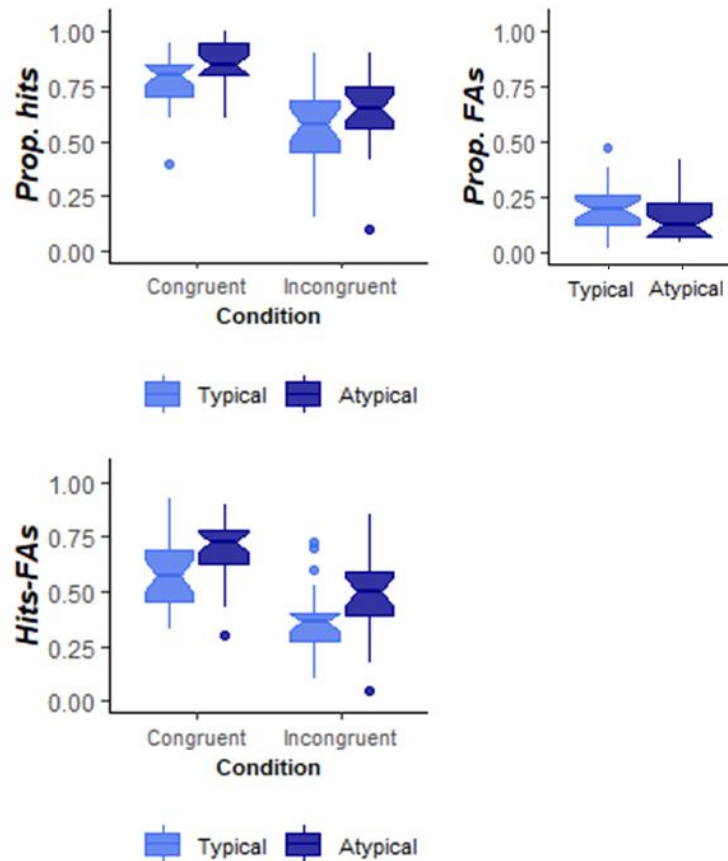
1 $F(1,25)=0.83, p=.37, \eta^2_p=.03$, but there was a significant interaction between congruency and typicality,
 2 $F(1,25)=25.00, p<.001, \eta^2_p=.48$, showing no difference in response time between typical and atypical
 3 items in the incongruent condition ($p=.41$), while typical items led to faster response times than atypical
 4 items in the congruent condition ($p<.001$).



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 6 Figure 2. Accuracy (left) and response times for correct trials (in ms, right) in the category verification task for
 7 congruent and incongruent trials across conditions of typicality

8 *Recognition memory task*

9 The ANOVA on hit rates with congruency (congruent, incongruent) and typicality (typical, atypical) as
 10 within-subject variables revealed that congruency at encoding impacted subsequent recognition, with
 11 higher hit rates for items that were congruent with the presented category than incongruent ones,
 12 $F(1,25)=80.19, p<.001, \eta^2_p=.76$. There was also a main effect of typicality, with higher hit rates for
 13 atypical than typical items, $F(1,25)=11.84, p=.002, \eta^2_p=.32$. The interaction between congruency at
 14 encoding and typicality was not significant, $F(1,25)=0.01, p=.95, \eta^2_p=.01$. The same analysis on high
 15 confidence responses only (level 4 of confidence) revealed the same pattern of results, with the main
 16 effect of congruency showing more hits for congruent than incongruent items, $F(1,25)=171.45, p<.001,$
 17 $\eta^2_p=.87$, a main effect of typicality with more high confidence hits for atypical than typical items,
 18 $F(1,25)=48.81, p<.001, \eta^2_p=.66$, and no interaction between congruency and typicality, $F(1,25)=0.01,$
 19 $p=.95, \eta^2_p=.01$ (Table 2). There was a significantly greater proportion of false alarms in the typical than
 20 atypical condition, $F(1,25)=4.74, p=.04, \eta^2_p=.16$. Finally, the ANOVA on the global performance index
 21 of Hits-FAs was characterized by the main effect of congruency at encoding, with better memory
 22 performance for items that were congruent than incongruent with the category at encoding,
 23 $F(1,25)=80.19, p<.001, \eta^2_p=.76$, and a main effect of typicality, with overall better recognition memory
 24 performance for atypical than typical items, $F(1,25)=20.43, p<.001, \eta^2_p=.45$. The interaction was not
 25 significant, $F(1,25)=0.01, p=.95, \eta^2_p=.01$ (see Figure 3).



1
 2 Figure 3. Proportion of hits (upper left), false alarms (FAs; right), and a global index of recognition memory (hits
 3 minus FA rates; lower left) across conditions

Table 2. Proportions of hits and FAs across confidence ratings

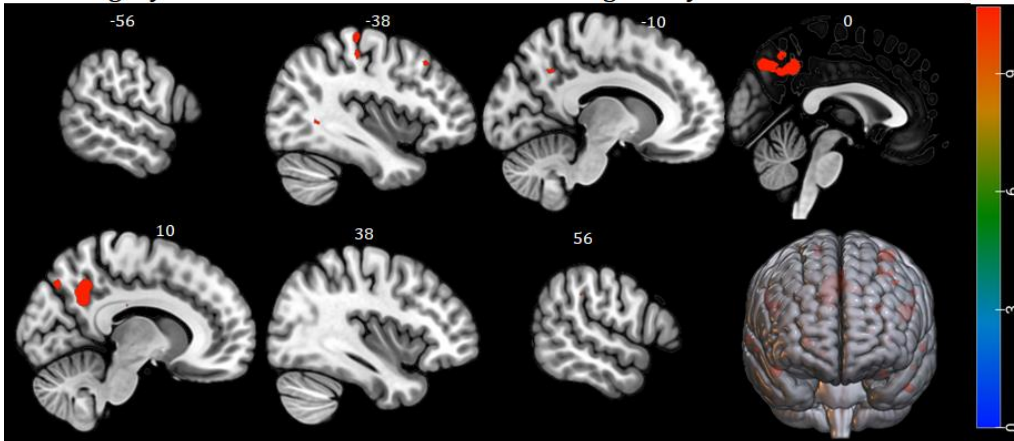
	Confidence 1		Confidence 2		Confidence 3		Confidence 4	
	Typical	Atypical	Typical	Atypical	Typical	Atypical	Typical	Atypical
Hits - congruent	0.01	0.01	0.04	0.04	0.14	0.09	0.57	0.70
Hits - incongruent	0.02	0.01	0.09	0.06	0.16	0.14	0.29	0.42
False alarms	0.02	0.01	0.07	0.03	0.06	0.05	0.03	0.05

4
 5 **Univariate fMRI results**

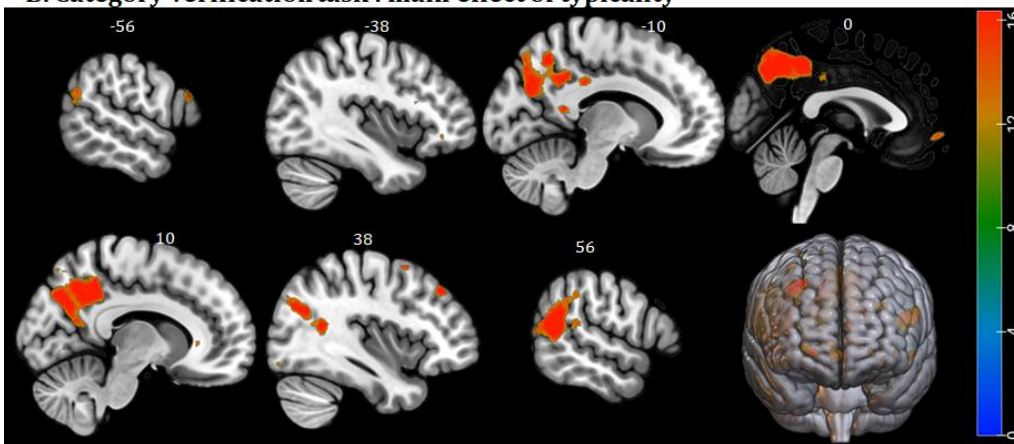
6 *Category verification task*

7 The factorial analysis showed a main effect of congruency such that items that were incongruent with
 8 the category (compared to congruent ones) elicited greater activation in the left postcentral gyrus and
 9 left middle temporal gyrus as well as in the right precuneus and the right angular gyrus. The main effect
 10 of typicality revealed greater activity for the typical than the atypical items in the bilateral angular gyrus,
 11 right middle frontal gyrus, medial prefrontal cortex and left precuneus, while the activation was greater
 12 for atypical than typical items in the left opercular part of the inferior frontal cortex. The congruency by
 13 typicality interaction revealed greater activation in the bilateral thalamus and bilateral precuneus for
 14 categorizing typical items compared to atypical items in the congruent condition, with no differences in
 15 typicality for the incongruent condition (Table 3 and Figures 4 and 5).

A. Category verification task : main effect of congruency



B. Category verification task : main effect of typicality



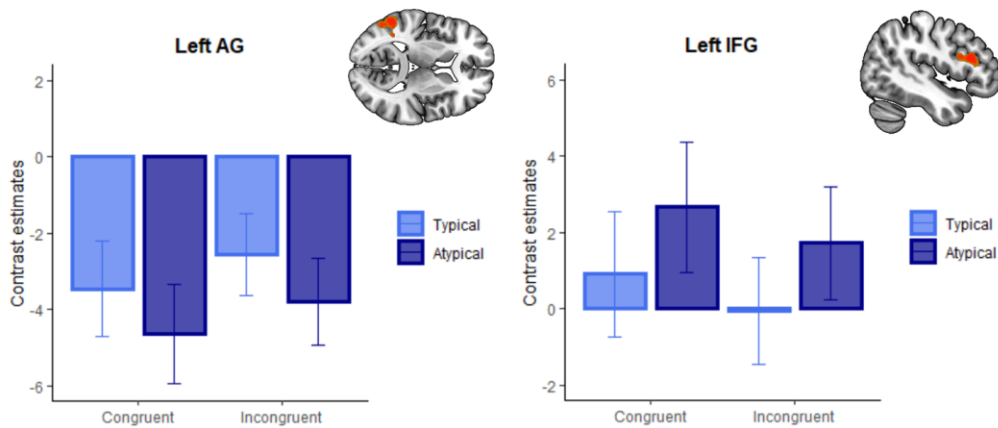
C. Category verification task : congruency x typicality interaction



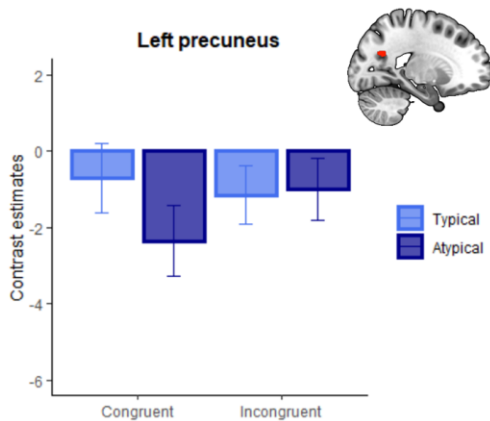
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Figure 4. Significant activation clusters in the category verification task

A. Category verification task : main effect of typicality



B. Category verification task : congruency x typicality interaction



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2 Figure 5. Contrast estimates in significant clusters of the A) typicality contrast, and B) interaction between
3 typicality and congruency, in the category verification task

4 *Recognition memory task*

5 During retrieval, old items relative to new items engaged more activation in the bilateral angular gyrus,
6 left precuneus, bilateral middle temporal gyrus, left temporal pole, medial prefrontal cortex and right
7 postcentral gyrus. In contrast, activation in the left supramarginal gyrus and right superior parietal lobule
8 was greater for new than old items. No region survived the statistical threshold of significance for the
9 typicality contrast or the interaction between memory status and typicality (Table 3, and Figures 6 and
10 7).

11

	Region hemisphere	MNI coordinates			F-value	k	
		x	y	z			
Category verification task							
<i>Main effect of congruency</i>							
	Middle temporal gyrus	L	-50	-50	22	23.08	276
	Precuneus	R	6	-54	34	22.49	648
	Postcentral gyrus	L	-34	-28	64	21.21	82
	Angular gyrus	R	48	-54	24	17.96	138
<i>Main effect of typicality</i>							
	Middle frontal gyrus	R	32	38	44	34.94	225
	Precuneus	L	-16	-68	22	32.05	2932
	Angular gyrus	R	48	-50	18	30.81	1777
	Opercular inferior frontal gyrus	L	-44	24	20	25.05	331
	Angular gyrus	L	-54	-60	22	19.52	146
	Medial prefrontal cortex	R	4	52	-8	17.99	88
<i>Congruency x typicality interaction</i>							
	Precuneus	R	10	-46	48	31.46	389
	Thalamus	L	-10	-16	16	23.70	128
	Precuneus	L	-20	-62	24	20.93	190
	Thalamus	R	8	-2	16	20.18	120
Recognition memory							
<i>Main effect of old/new status</i>							
	Angular gyrus	L	-38	-72	36	48.69	1540
	Precuneus	L	-8	-64	28	44.95	3477
	Middle temporal gyrus	R	66	-36	-12	28.24	128
	Angular gyrus	R	38	-70	46	25.27	569
	Supramarginal gyrus	L	-34	-38	40	24.04	170
	Medial prefrontal gyrus	R	6	46	10	21.85	807
	Middle temporal gyrus	L	-64	-38	-10	20.35	95
	Angular gyrus	R	54	-58	20	20.24	178
	Temporal pole	L	-24	64	10	19.29	123
	Postcentral gyrus	R	28	-42	44	19.16	168
	Superior parietal lobule	R	18	-64	54	18.01	79

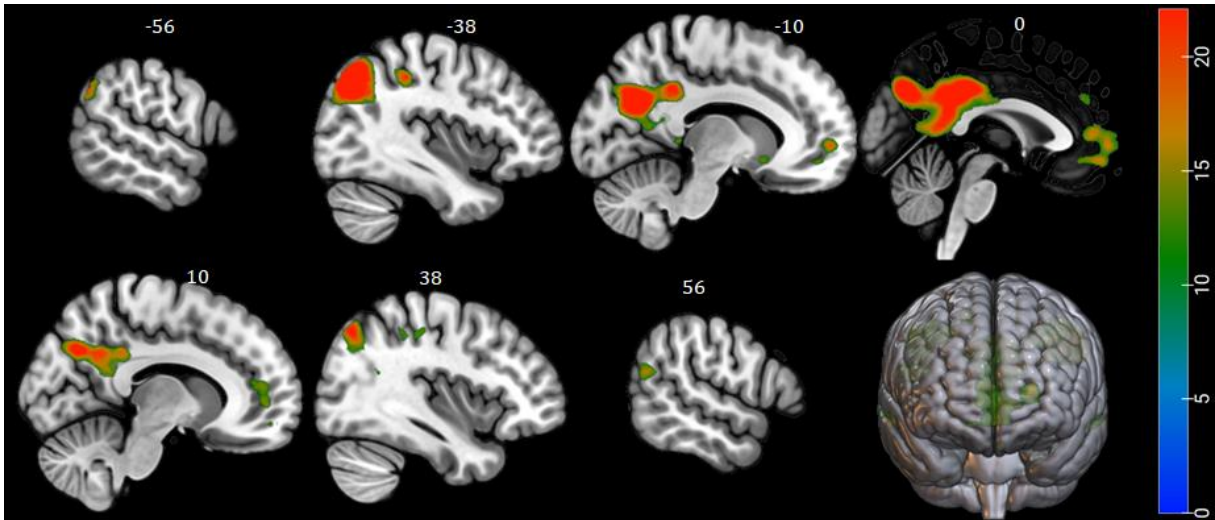
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Table 3. Univariate analyses: Peak coordinates of the significant clusters observed in the category verification

3

and recognition memory tasks



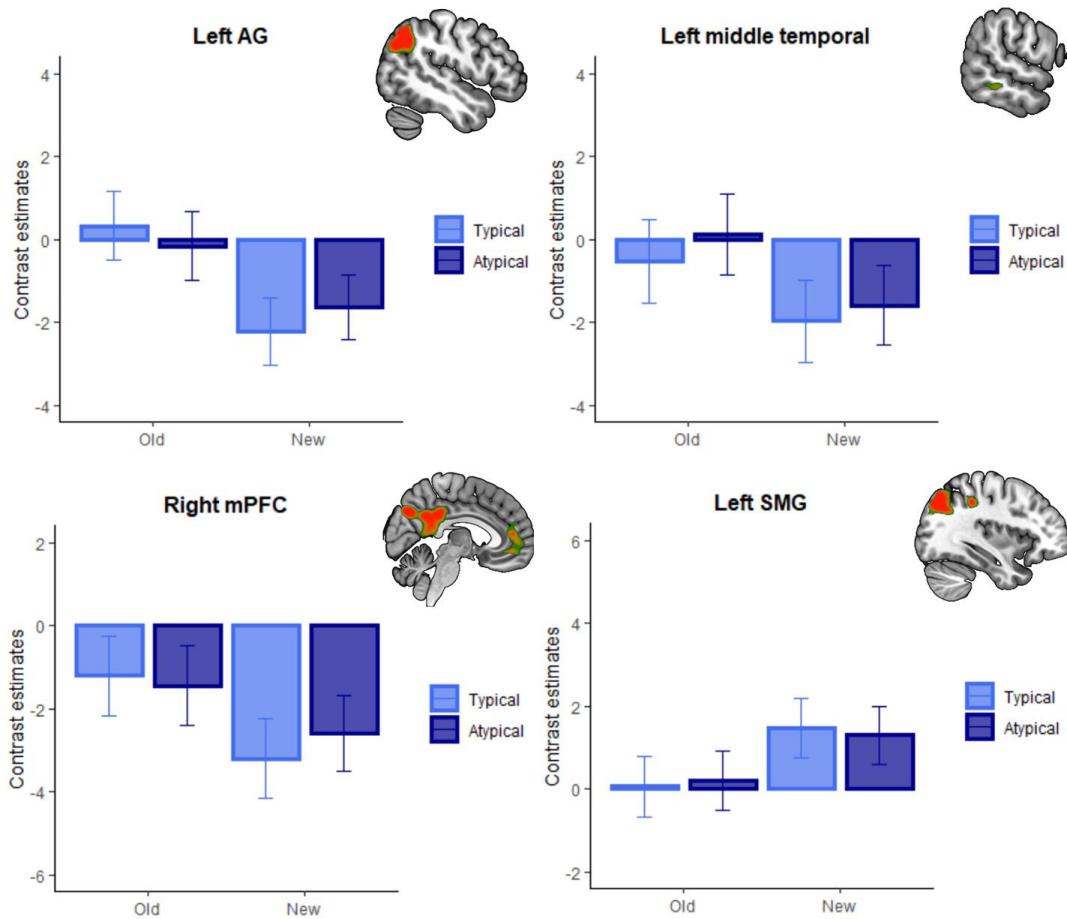
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Figure 6. Clusters showing significant activations in the old/new contrast of the recognition memory task

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Recognition memory task: main effect of memory status



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Figure 7. Contrast estimates in significant clusters of the old/new contrast in the recognition memory task

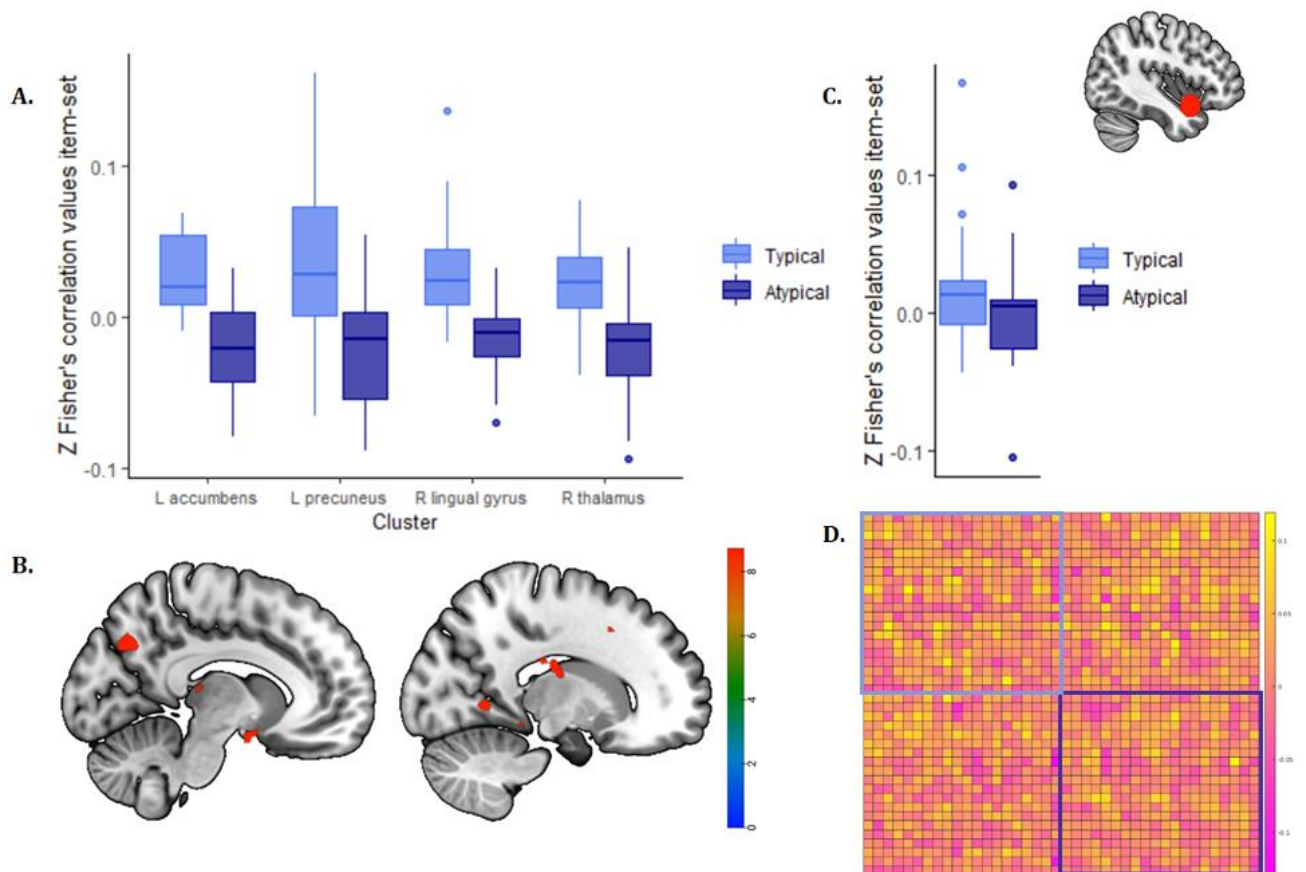
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Representational Similarity Analyses

We conducted a factorial ANOVA on ERS values maps with typicality (typical, atypical) and level (item, set) as factors. Results yielded a significant interaction in the left precuneus, left nucleus accumbens, right lingual gyrus, and right thalamus. This interaction showed that, in these regions, item values were higher than set values for typical items, but not for atypical items, suggesting that the reinstatement of item-specific patterns of brain activity during retrieval was only observed for typical items (Figure 8A and 8B). The reverse contrast did not show any clusters above the significance threshold.

Finally, the same analysis within our ROI in the ATL showed a significant interaction reflecting reinstatement for typical items, but not for atypical ones (Figure 8C).



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Figure 8. A. Item-set Fisher's Z correlation values of the clusters showing significant ERS patterns for typical and atypical items in searchlight analyses; B. Illustration of the significant clusters in searchlight analyses; C. Item-set Fisher's Z correlation values of the significant ERS patterns for typical and atypical items in the ATL

- 1 ROI analysis; D. Heatmap illustrating Fisher-Transformed Pearson correlations of ERS values in the left
- 2 precuneus. Typical items are indicated by a light blue rectangle, and atypical items by a dark blue rectangle
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1 **Discussion**

2 Despite the importance of concept typicality in the organization of semantic memory, and the influence
3 semantics bears on episodic memory, still little is known about how typicality influences episodic
4 memory and what are its neural correlates. Our study examined the neural correlates associated with
5 item typicality during a semantic category verification task and a subsequent episodic recognition task,
6 and investigated the similarity in the patterns of activation associated with the reinstatement of typical
7 and atypical items from encoding to retrieval.

8 *Semantic typicality effects*

9 Behaviorally, the results of this study are in line with the existing literature by showing that typical items
10 are categorized better and faster than atypical items, particularly in the congruent condition, i.e. when
11 the item belongs to the presented category (Kiran et al., 2007). This indicates that the greater number of
12 features typical items share, compared to atypical items, benefits semantic categorization. These
13 behavioral effects were accompanied by greater activation for typical items in the bilateral AG, right
14 frontal regions and the left precuneus. Activation was instead greater for atypical than typical items in
15 the left IFG.

16 Contrary to most studies, we did not find semantic typicality effects in the ATL (Santi et al., 2016,
17 Woollams, 2012, Woollams et al., 2008). Yet, we observed typicality effects in this region during
18 reinstatement of encoding patterns at retrieval, leading us to believe that the ATL was not insensitive to
19 typicality. This result is discussed below.

20 Beyond the ATL, our study replicated Santi et al.'s (2016) results of greater activation for atypical items
21 in the left IFG, as well as greater activation for typical items in the right middle frontal gyrus and the
22 bilateral precuneus. In addition, our study revealed significant recruitment of the right AG during the
23 processing of typical items, corroborating Reilly et al.'s (2019) results of sensitivity to feature
24 distinctiveness in the left IFG, and to feature sharedness in the right AG (though results from Reilly et
25 al. did not survive multiple comparisons correction). The involvement of the IFG in the semantic
26 processing of atypical items supports the hypothesis that this region plays a role in semantic control and
27 semantic selection (Badre et al., 2005; Marques, 2007). Specifically, greater semantic control is
28 necessary to correctly categorize atypical items due to the lower number of features they share. Besides,
29 distinctive features of an atypical item must be suppressed to decide if it belongs to the category (Santi
30 et al., 2016). In addition, our results are consistent with the idea that the AG is implicated in semantic
31 processing, possibly working as a cross-modal semantic hub, binding the features commonly associated
32 with typical concepts (Bonner et al., 2013; Seghier, 2013).

33 *Episodic old/new effects*

1 Turning to the recognition memory task, correct recognition of old items relative to new ones involved
2 an important network of regions belonging to the *core recollection network* (i.e., the left PC, bilateral
3 AG, middle temporal gyrus and medial prefrontal cortex, mPFC), which is a content-independent
4 network engaged when a retrieval cue elicits recollection and known to mediate the successful retrieval
5 of episodic memories (Rugg & Vilberg, 2013). In addition, more recent fMRI studies have consistently
6 shown that these regions track the strength or precision of recollection based on the richness of memory
7 representations (Sreekumar et al., 2018), through vividness ratings (Richter et al., 2016; St-Laurent et
8 al., 2015; Tibon et al., 2019), remember judgments (Wang et al., 2016), confidence judgments (Qin et
9 al., 2011), metacognitive decisions (Baird et al., 2013), context-dependent retrieval (Bonnì et al., 2015),
10 as well as mental imagery processes accompanying episodic memory retrieval (Gardini et al., 2006).

11 Interestingly, recognition of old items recruited the left temporal pole and bilateral middle temporal
12 gyrus, two regions that are considered as part of the ATL (Bonner & Price, 2013), and thus, a key hub
13 in the semantic network. These results may suggest that the ATL is involved in the processing and
14 retrieval of object concepts (regardless of their typicality). The PC, AG and mPFC are thought to play a
15 role in post-retrieval monitoring processes, assessing the accuracy in attributing an experience to the
16 past (mPFC) and the strength of recollection (AG), thus possibly contributing to the production of
17 confidence ratings (Baird et al., 2013; Qin et al., 2011; Rugg & Vilberg, 2013; Sreekumar et al., 2018).

18 *Episodic typicality effects*

19 Behaviorally, in line with the existing literature, we found greater recognition accuracy for atypical than
20 typical items, and higher confidence judgments in their correct recognition (Alves & Raposo, 2015;
21 Souza et al., 2021). Contrary to the semantic category verification task, this suggests that the higher
22 number of shared features in typical items hampered their recognition, possibly because of the inherent
23 confusability of items, i.e., they share more features. Indeed, the distinctiveness of atypical items led to
24 a higher recognition rate (hits), while typical items led to greater false alarm rates, possibly due to their
25 greater confusability. Yet, these behavioral differences were not associated with different patterns of
26 neural activation in the univariate analyses, although they were associated with differences in their
27 reinstatement patterns, as assessed through ERS analyses. Indeed, one advantage of RSA-based analysis
28 is that it treats all items in the design individually, thereby providing finer insights on their relationships
29 and associated patterns of activation, rather than contrasting items grouped by condition as classically
30 done in univariate analysis (Dimsdale-Zucker & Ranganath, 2018).

31 We found greater reinstatement from encoding to retrieval for typical than atypical items in the left
32 accumbens, left PC, right lingual gyrus and right thalamus. These results favor the idea that typical items
33 which share more features and are so more confusable, require greater reinstatement to reach successful
34 retrieval. Presumably, reinstatement helps to overcome the interference arising from distractors with
35 whom typical items share many features. Interestingly, reactivation of the left PC is in line with the role

1 of this region in both episodic and semantic processing (Binder et al., 2009) and more specifically its
2 function in coding conceptual representations. Notably, Fairhall and Caramazza (2013) and Liuzzi et al.
3 (2020), showed that, in a typicality judgement task, semantically more similar categories also display
4 more similar neural patterns in the PC, which makes it a candidate region for the supramodal
5 representation of the conceptual properties of objects. We extend this effect to retrieval, by showing
6 greater reinstatement of semantic encoding processes for typical items which are conceptually more
7 similar than atypical objects. Yet, here, contrary to previous studies, the PC showed similarity patterns
8 not at the category-level, but at the item-level. So, the role of the PC in reinstating conceptual processing
9 during episodic decisions remains open and needs to be explored further in future research.

10 Importantly, our ROI analysis showed evidence for reinstatement in the left ATL, which is thought to
11 be a central hub integrating features into complex representations of objects (Bruett et al., 2020;
12 Bruffaerts et al., 2019; Coutanche & Thompson-Schill, 2015). This result corroborates extensive
13 literature showing links between items similarity, as indexed by the features they share or make them
14 distinctive, and the similarity of activation patterns in the ATL (Bruffaerts et al., 2013; Chen et al., 2016;
15 Clarke, 2020; Clarke & Tyler, 2014; Fairhall & Caramazza, 2013; Liuzzi et al., 2015; Martin et al.,
16 2018). Importantly, this result seems to be robust across different types of processes, as long as they
17 require fine-grained representations, i.e., from semantic decisions to episodic discrimination like in this
18 task.

19 To conclude, item typicality influences category verification through differential activations in IFG and
20 AG consistent with prior work. Furthermore, item typicality modulates episodic memory through
21 differential patterns of reinstatement in several regions including the left PC and ATL. Future research
22 is still needed to better understand the role of the left PC in semantic processing and episodic
23 reinstatement of semantic information, as well as to investigate the replicability of these findings across
24 different materials, such as visual items.

25

1 Declaration of interest: none

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