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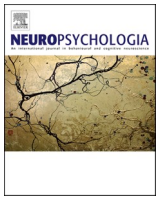

Total recall: Detecting autobiographical memory retrieval in the absence of behaviour

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ABSTRACT

Functional neuroimaging has fundamentally changed our understanding of disorders of consciousness (DoC). While many DoC patients exhibit minimal to no *behavioural* responsiveness, a significant minority show *neural* evidence of awareness and preserved cognitive functioning. Although several cognitive functions have been explored in DoC patients, autobiographical memory – the ability to form and retrieve personal memories – has yet to be investigated. To address this gap, we used functional magnetic resonance imaging (fMRI) to investigate autobiographical memory in one DoC patient. The patient viewed video clips across three conditions: (1) *Own* - clips recorded from their perspective during a recent mall visit; (2) *Other* - clips from a healthy control's visit to the same mall; and (3) *Bookstore* - novel clips from an entirely different store that had not been visited. We trained a linear support vector classifier to associate fMRI activity in canonical autobiographical memory regions with each condition using data from twelve healthy participants. We then applied the trained model to the patient's data to 'decode' which condition their fMRI activity predicted. The model accurately distinguished between *Own*, *Other*, and *Bookstore* conditions in the patient (*Balanced Accuracy* = 0.448, $p = .032$), with performance within the control group range ($p = .068$). Similarly, the model distinguished between the *Own* and *Other* conditions above chance (*Balanced Accuracy* = 0.609, $p = .032$) and within the control group's distribution ($p = .620$), suggesting that the patient was still able to differentiate personal experiences from visually similar scenes, despite being behaviourally unable to report that this was the case. These findings provide preliminary evidence that autobiographical memory processes, critical to conscious awareness and identity, remain intact in some DoC patients, shedding further light on their covert capabilities and inner experiences.

1. Introduction

Disorders of consciousness (DoC) refer to a spectrum of neurological impairments that result from severe brain injury. Patients with DoC, like the minimally conscious state or Unresponsive Wakefulness Syndrome (otherwise known as the vegetative state), show clear signs of physiological arousal ('wakefulness') but often exhibit minimal or inconsistent evidence of awareness. Critically, DoC diagnoses rely entirely on observable behaviour. Patients showing limited but reproducible signs of awareness are typically diagnosed as minimally conscious, while those who remain unresponsive during behavioural assessment are diagnosed with Unresponsive Wakefulness Syndrome – a state of wakefulness *without* awareness (Georgiopoulos et al., 2010; Giacino et al., 2002, 2009; Jennett and Plum, 1972). However, accurately diagnosing DoC on the basis of behaviour alone is immensely difficult. Sensory or motor impairments can make patients appear to be

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behaviourally unresponsive even when awareness is partially or entirely preserved (Kondziella et al., 2016; Monti et al., 2010; Owen et al., 2006). In fact, previous research has shown that profound motor dysfunction can present like Unresponsive Wakefulness Syndrome while sparing awareness altogether – a phenomenon termed Cognitive Motor Dissociation or covert awareness (Fernández-Espejo et al., 2015; Pincherle et al., 2021).

Functional neuroimaging has emerged as a powerful tool for detecting covert awareness in behaviourally non-responsive DoC patients (Berlingeri et al., 2019; Owen, 2013). Neuroimaging-based assessments that use functional magnetic resonance imaging (fMRI; Owen et al., 2006), electroencephalography (EEG; Cruse et al., 2011), and, most recently, functional near-infrared spectroscopy (fNIRS; Kazazian et al., 2024) have uncovered sensory and cognitive capabilities that were otherwise inaccessible using conventional clinical tools. For example, while standardized diagnostic assessments can only *infer* preserved higher-level cognitive processes from behavioural responses, neuroimaging-based assessments can identify a rich set of cognitive processes such as bottom-up and top-down attention, language comprehension, plot-following, and command following (Chatelle et al., 2020; Gibson et al., 2016; Laforge et al., 2020; Monti and Owen, 2010; Naci et al., 2014; Owen et al., 2006). Nevertheless, one critical domain that has not been explored in such patients is autobiographical memory.

Autobiographical memory, the ability to form and recall episodic memories, is a central pillar of everyday waking consciousness (Behrendt, 2013; Prebble et al., 2013). It plays a crucial role in shaping our sense of identity both in the present and over time (Prebble et al., 2013; Tulving, 1985, 2002) and serves as a primary mechanism through which disparate sensory and cognitive processes connect to the self. Several key brain regions are involved in supporting these complex functions, including the prefrontal cortex, the hippocampus and surrounding cortices, the posterior cingulate, retrosplenial cortex, and the angular gyrus (Shepardson et al., 2023). Additional regions, such as the medial and lateral temporal cortices, temporal-parietal junction, and cerebellum, also contribute to autobiographical memory retrieval (Svoboda et al., 2006). Many of these areas overlap with the so-called 'default mode network', which facilitates self-referential processing and integrates contextual details – such as emotional valence and social content – into memory (Fuentes-Claramonte et al., 2019; Katsumi et al., 2024; Raichle, 2015).

Some patients who have recovered from a DoC have retrospectively reported having autobiographical memories of their experiences (Fernández-Espejo and Owen, 2013; Owen, 2017; Taylor et al., 2020) and in other studies of such patients, intact autobiographical memory can be strongly inferred (Monti and Owen, 2010; Naci and Owen, 2013; Owen et al., 2006). Yet, whether a patient is actually able to lay down and retrieve autobiographical memories *while in* a behaviourally non-responsive state is difficult to determine because it is an inherently subjective phenomenon that is largely dependent on self-report (Rabinowitz and Levin, 2014). Additionally, even mild traumatic brain injuries can cause detectable impairments in memory performance (Dikmen et al., 1987; Hart and Sander, 2017) while moderate to severe brain injury significantly increases the risk of protracted cognitive and affective deficits, particularly related to memory (Shuanglong et al., 2024). However, the fact that substantial overlap exists between the brain regions associated with autobiographical memory and those supporting awareness, particularly the default mode network (e.g., Threlkeld et al., 2018; Bodien et al., 2019), it seems likely that some covertly aware behaviourally non-responsive DoC patients also retain the neural capacity to support autobiographical memory.

To investigate autobiographical memory in a DoC patient, we measured their neural activity using fMRI during a novel, passive (i.e., response-free) task. Specifically, the patient viewed three sets of video clips: (1) clips recorded from their perspective during a recent visit to a local mall, (2) similar clips from a control participant's visit to the same mall, (3) novel clips from a different environment. We examined the patient's hemodynamic activity across these three conditions and compared it to data from a cohort of healthy controls who underwent the same procedure (Erez et al., 2021). We applied a machine learning classification approach to 1) identify the brain regions that were most associated with naturalistic autobiographical memory retrieval in healthy controls and 2) determine whether the patient produced comparable neural activation patterns. We hypothesized that if the patient produced maps of neural activation comparable to healthy controls when viewing scenes from their own life, this would provide evidence of their preserved ability to encode and recall novel (i.e., post-injury) autobiographical memories.

2. Methods

2.1. Participants

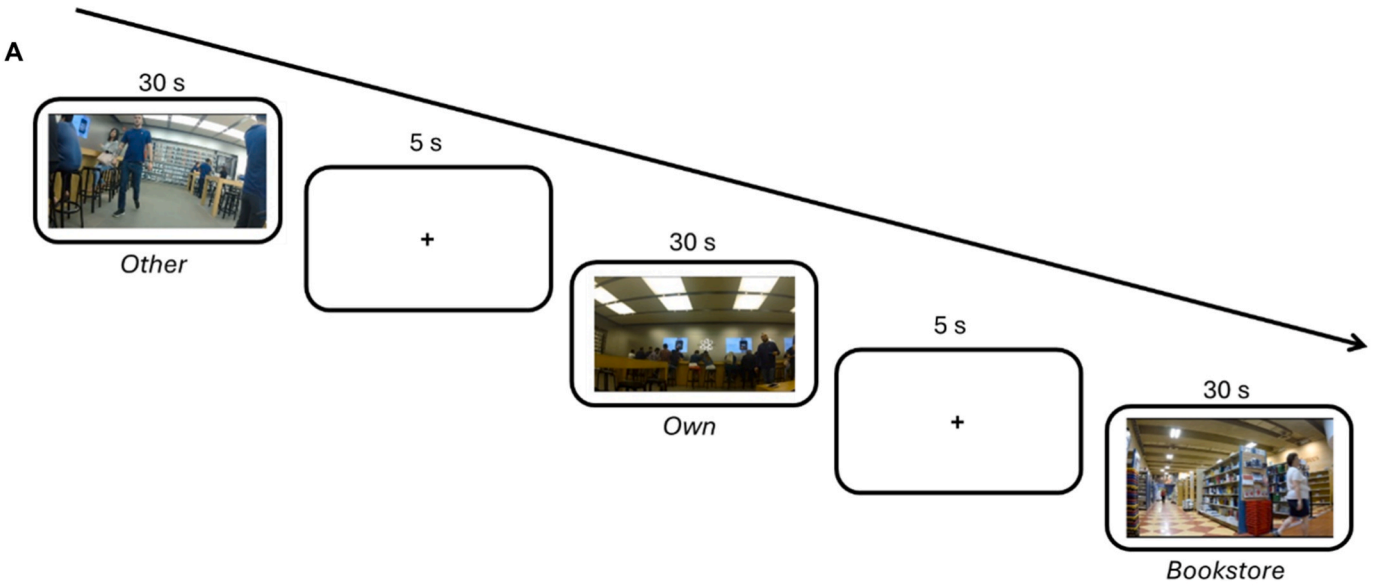
We included data from twelve healthy volunteers (Mean age = 25, Range = 20–34; 6 females) previously collected in a published study (see Erez et al., 2021 for more details) to serve as the control group for this study. We also enrolled two DoC patients but excluded one because they were unable to lie flat in the scanner. This left one DoC patient (Age = 29; female; see the results for clinical information) and twelve healthy volunteers who completed the study. All healthy volunteers provided written informed consent and received compensation for their time, while the patient's substitute decision maker provided written assent. The Health Sciences Research Ethics Board and Psychology Research Ethics Board at Western University provided ethical approval for the study.

2.2. Procedure and design

We first administered the Coma Recovery Scale-Revised (CRS-R) behavioural assessment to measure the patient's arousal and level of overt awareness prior to the task (Giacino et al., 2004). Next, we seated the patient in a wheelchair and took them on a route through two stores (the Apple Store and the Bay) at a local shopping centre in London, Ontario, Canada. We attached a forward-facing camera to the wheelchair to record audiovisual details during the visits. The twelve controls went through exactly the same procedure, including being wheeled through the two stores of the mall and remaining silent and non-responsive as though they were a DoC patient. The visit to each store lasted approximately 20 minutes. Throughout the visit, both healthy controls and the patient were asked to refrain from moving their head or body and focus on the events directly in front of them.

For both healthy controls and the patient, we divided each mall visit recording into 30-s clips for use in the scanning session. We categorized these recordings into three conditions: *Own* videos (autobiographical videos from the patient or control's own recordings at the mall), *Other* videos (for the patient, recordings from a random selection of healthy controls recorded at the same locations; for the controls, recordings from other healthy controls instead of themselves), and *Bookstore* videos (recordings from a visually similar but novel location that neither the patient nor the controls had ever visited; see Fig. 1A). We instructed all participants, including the patient, to simply watch and listen to the videos, with no overt behavioural response required while in the fMRI scanner. The fMRI data was acquired approximately a week (*Mean* = 6 days) after the mall visit.

Both the controls and the patient viewed 96 video clips in total (32 from their *Own* visit, 32 from the *Other* condition, and 32 from the *Bookstore* condition). We sorted these clips across six blocks, each consisting of 16 videos, with a 5-s inter-stimulus interval between each clip. We randomized the presentation order, with the exception that each video was shown twice during the scanning session (once in the first three blocks and once in the last three blocks). We excluded any video clips that contained the participant's body parts or other obvious identifiers.



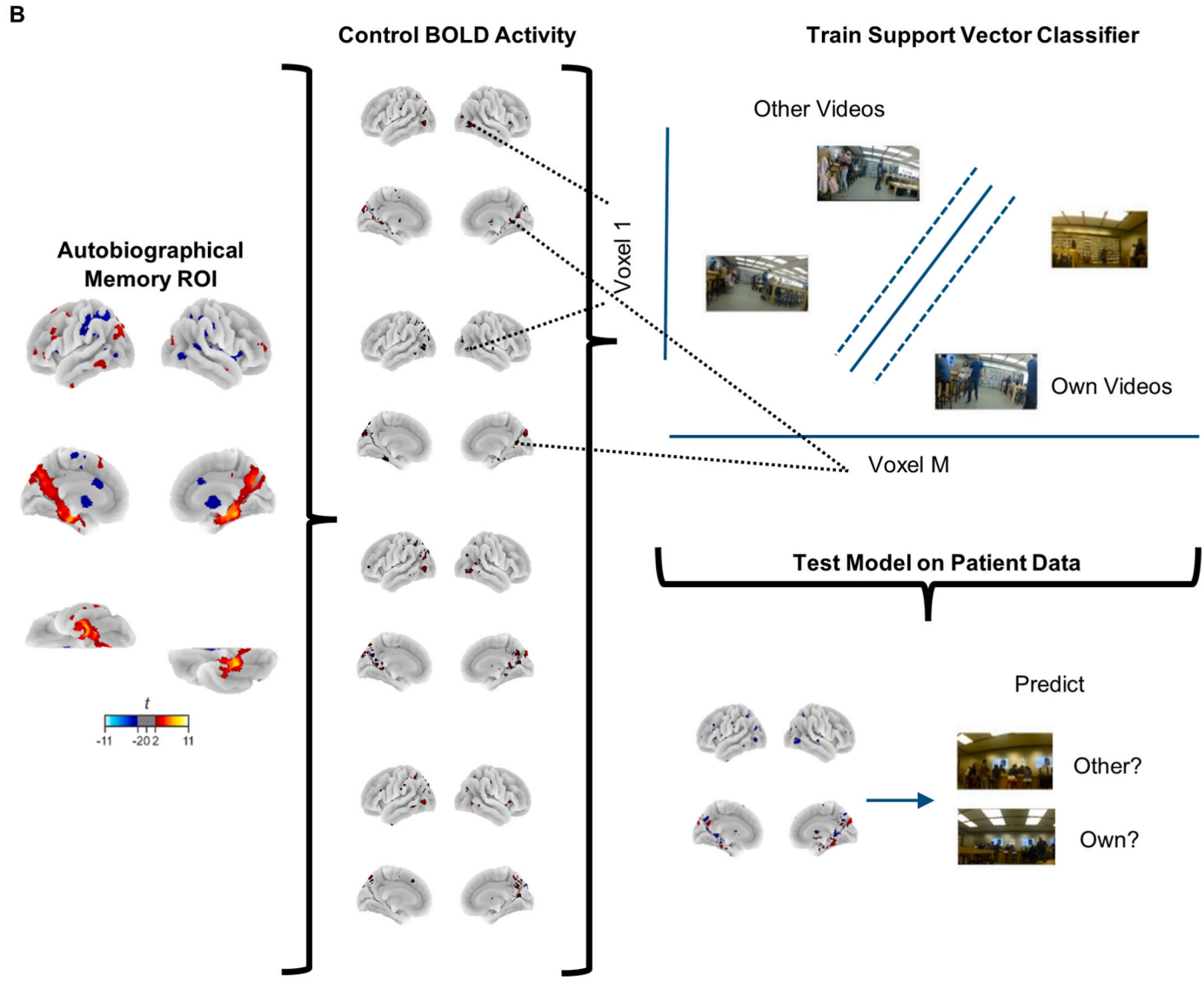


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Fig. 1. A: A schematic of the experimental design. Participants viewed video recordings from one of three autobiographical memory conditions: *Own* videos (the participant's own recordings at the mall), *Other* videos (recordings from another participant at the same locations), and *Bookstore* videos (recordings from a visually similar but novel location). Each of the 96 clips lasted 30 s, followed by a 5-s inter-stimulus interval. Figure adapted from Erez et al. (2021). **B:** A schematic of the data analysis steps taken to investigate autobiographical memory in the patient. We used a region of interest (ROI) associated with autobiographical memory from the online meta-analysis tool NeuroQuery (Dockès et al., 2020). We used this ROI to mask both patient and control data ($|t| > 2.5$). We then trained a linear support vector classifier to use the trial-averaged BOLD activity to distinguish between the autobiographical memory conditions (in the case of this figure, between *Own* and *Other* conditions). We then applied that model to the patient's data and calculated how accurate the model was at predicting the different autobiographical memory conditions.

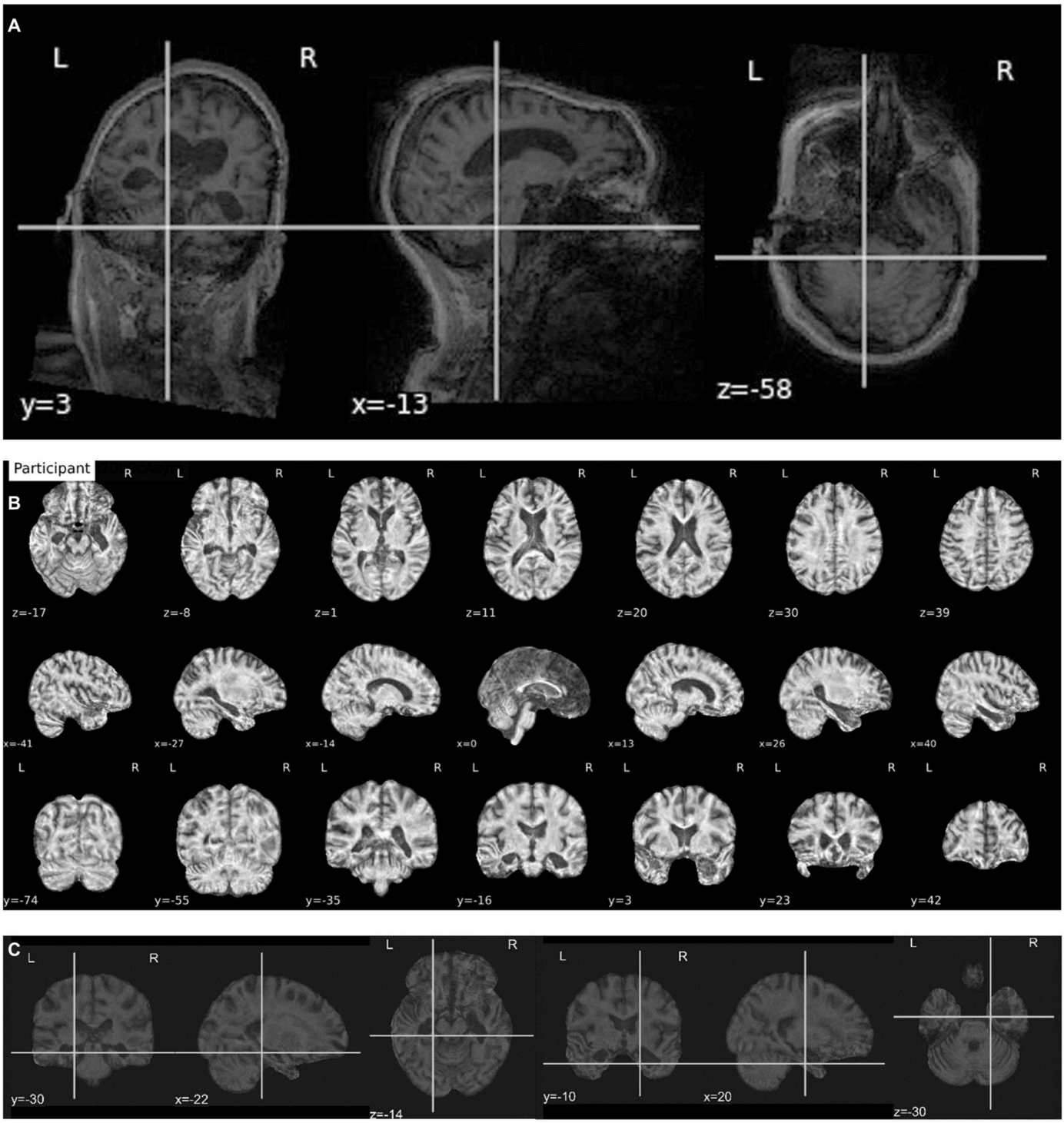

Fig. 2. A: An anatomical MRI of the DoC patient. **B**: The patient's preprocessed anatomical scan registered to MNI space (generated using fMRIPrep). There is a noted loss of grey matter that is prevalent across several brain areas. **C**: Cross section of the hippocampus in MNI space. While adjacent temporal regions show atrophy, the hippocampus appears relatively spared.

2.3. fMRI data acquisition

We scanned all participants on a Siemens Tim Trio 3 T MRI scanner at the Robarts Research Institute at Western University. The structural scan was a T1-weighted magnetization-prepared rapid-gradient echo (MP-RAGE) with a 1 mm isotropic voxel size and echo time of 3 ms. We obtained the functional volumes using a T2*-weighted whole-brain echo-planar imaging (EPI) sequence. Each EPI volume consisted of 48 axial slices, acquired in an interleaved manner (TR = 1000 ms; TE = 30 ms; flip angle = 40°; FoV = 208 mm; voxel size = 2.5 mm isotropic).

2.4. fMRI preprocessing

We preprocessed the functional and structural scans using *fMRIPrep* 22.0.2 (Esteban et al., 2019; Gorgolewski et al., 2011). For detailed preprocessing steps (automatically generated by fMRIPrep), see the Supplementary Materials. Briefly, we applied standard preprocessing to the T1-weighted image, including intensity non-uniformity correction, skull-stripping, segmentation, and normalization to a standard template (ICBM 152 Nonlinear Asymmetrical Template (Version, 2009c). For the T2*-weighted images from each run, we first referenced the volumes to representative volumes, estimated motion parameters and transformation matrices, realigned the volumes, applied slice timing correction, co-registered the volumes to the native T1-weighted image, estimated nuisance regressors and then resampled to MNI space. We regressed out the noise confounds (i.e., motion, global signal, and physiological signals) from the resulting blood oxygen level dependent (BOLD) time series prior to any subsequent analysis and followed that with spatial smoothing using a Gaussian kernel (FWHM = 4 mm). We performed several quality assurance checks to ensure that this preprocessing pipeline was suitable in the case of our patient, where standard preprocessing may be insufficient because of structural abnormalities expected following traumatic brain injury (see Fig. 2 for the original and spatially registered anatomical scans). Despite the damage, spatial registration and data quality were well within acceptable ranges.

2.5. fMRI decoding analyses

We used a machine learning approach to perform two 'decoding' analyses. The primary aim of these analyses was to construct a model using fMRI data from autobiographical regions in the controls that we could then apply to distinguish between the patient's: (1) *Own*, *Other* and *Bookstore* conditions and (2) *Own* from *Other* conditions. To ensure that our decoding analysis focused on autobiographical memory processes, we used an ROI from the neuroimaging meta-analysis platform NeuroQuery (Dockès et al., 2020). The keyword "autobiographical memory" produced a mask of canonical autobiographical regions, such as the hippocampus, parahippocampal gyrus, precuneus, posterior cingulate, dorsal prefrontal cortex, and the extrastriate visual cortex generated from 523 studies (see Fig. 1B for the ROI). After extracting this ROI for each participant, we averaged the BOLD response within each trial, producing a total of 32 training examples per condition. We then standardized the BOLD response for each participant and voxel.

To determine which pattern of fMRI activity predicted each autobiographical memory condition, we used a linear Support Vector Classifier (SVC; Hearst et al., 1998). Before applying the model to the patient's data, we independently trained and optimized the SVC on control data using a Bayesian optimization framework (Bergstra et al., 2013). Specifically, we optimized the SVC to find the highest average leave-one-participant-out balanced accuracy score. During fifteen optimization rounds, we trained the model on all but one control participant and tested it on the left-out participant. We calculated the balanced accuracy (the arithmetic mean of the sensitivity and the specificity) for each left-out participant and averaged it across participants for each optimization round. The optimization objective was to find the set of SVC hyperparameters that maximized this average. The optimized hyperparameters were the regularization parameter *C*, the loss function (hinge or squared hinge), the number of iterations to train the model, the stopping criteria, and intercept scaling. Note that the optimization procedure occurred entirely using healthy control data, thus preventing the model from bias introduced by including the patient's data. Finally, we tested whether the optimized model could accurately classify the experimental condition based on the patient's data, using balanced accuracy to evaluate the model's performance.

To statistically evaluate the model's accuracy, we used permutation testing. Permutation testing is a non-parametric approach that accurately estimates the 'true' chance level by constructing null distributions of the model's accuracy based on the original data (Combrisson and Jerbi, 2015; Nichols and Holmes, 2002). Specifically, we retrained and retested the optimized model after randomly reshuffling the condition labels (i.e., *Own*, *Other, Bookstore*) across trials. We repeated this approach for 1000 iterations, obtaining a distribution of balanced accuracy scores. We used these null distributions to calculate *p*-values and *Z* scores for the model's accuracy for both decoding analyses.

To investigate which brain areas were driving the decoding performance, we performed two feature importance computations. First, we computed feature importance as a product of the weights of the trained model and the average BOLD activity. We computed this measure for each condition and averaged it across all trials and participants. For ease in interpreting feature importance, we used permutation testing to generate null distributions of feature importance expected by chance. We then used these distributions to convert the original feature importance to a *Z* score with a corresponding *p*-value. This approach has the benefit of allowing us to evaluate feature importance on the trained model, on the left-out patient data, and for both 2-class and 3-class decoding. To identify the voxels that significantly contributed to the model's performance, we applied false-discovery rate correction to these *p*-values using the max-*t* approach (Nichols and Holmes, 2002). For the second feature importance calculation, we performed recursive feature elimination. This involved calculating the balanced accuracy and deriving the model weights while keeping different percentiles of voxels (100, 90, 80, 70, 60, 50, 40, 30, 20, 10, 5, 1) in the model. Recursive feature elimination works by iteratively removing the voxel with the smallest weight (inferred as having the lowest ability to discriminate between conditions) which repeats until the specified percentile is reached. This process thus ranks the voxels based on when they are removed from the model. We then tested the model at each percentile on the patient's data to see if removing different percentiles of voxels affected the balanced accuracy. We inferred feature importance from the voxels that led to the highest balanced accuracy on the patient's data.

3. Results

3.1. Patient's clinical history

The patient suffered a traumatic brain injury after being struck by a car while cycling. She sustained a left epidural hemorrhage and pneumocephalus as well as several fractures, including a right orbital wall (both medial and lateral) fracture, an undisplaced left C6 facet fracture, a left sacrum fracture, bilateral temporal bone fractures, and a right petrous bone fracture. The patient underwent an epidural hematoma evacuation bilaterally and a right craniotomy following post-craniotomy hemorrhages. The mall visit occurred approximately four years (1448 days) post-injury and the fMRI session occurred 8 days later.

We performed the CRS-R (Giacino et al., 2004) on three separate occasions. During the initial family meeting (approximately 6 months before the study), the patient scored 3 (1A, 0V, 0M, 0O, 0C, 2R) corresponding to a diagnosis of Unresponsive Wakefulness Syndrome. During the mall visit, the patient scored a 5 (0A, 3V, 0M, 0O, 0C, 2R) showing evidence of visual tracking – corresponding to a diagnosis of minimally conscious state. Approximately 5 months following the fMRI assessment,

we tested the patient again and she scored 5 (1A, 1V, 0M, 1O, 0C, 2R) resulting again in a diagnosis of Unresponsive Wakefulness Syndrome.

The patient's anatomical scan at the time of the study (shown in native T1w space in Fig. 2A and MNI space in Fig. 2B) showed extensive grey matter loss, particularly bilateral damage to the temporal lobes. However, the hippocampus, a key autobiographical memory region in the medial temporal lobes, appeared to be relatively spared (see Fig. 2C).

3.2. Decoding results

3.2.1. Bookstore vs other vs own

First, we confirmed in controls that the model trained on fMRI

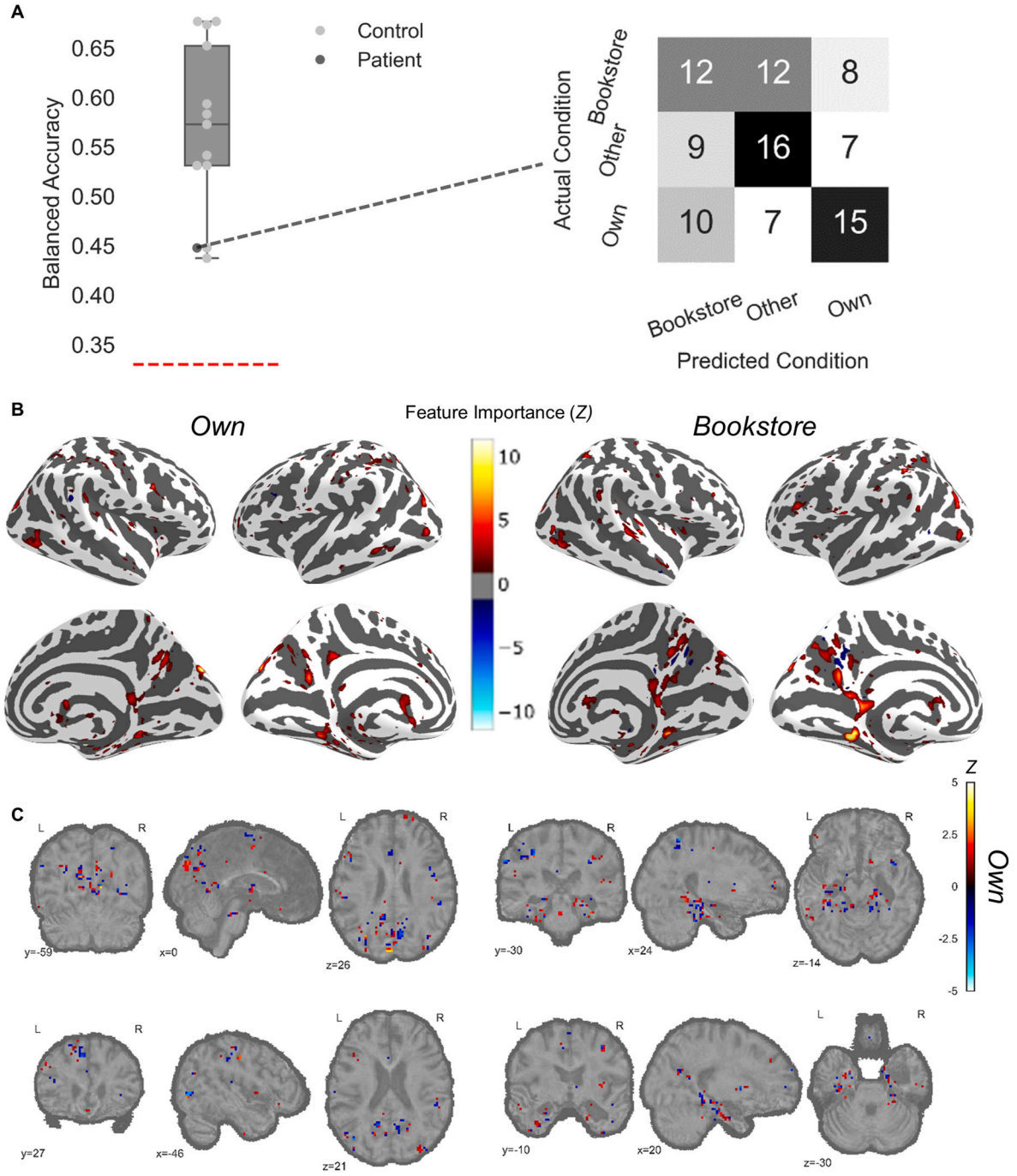

Fig. 3. **A:** A boxplot showing the distribution of balanced accuracy scores across participants when the model decoded between *Own, Other,* and *Bookstore* conditions. Individual dots indicate the balanced accuracy of each participant with the dark grey dot reflecting the patient's score. The confusion matrix shows the number of trials in each condition that was predicted by the model (when tested on the patient) and whether that prediction was accurate or inaccurate. **B:** Surface renderings showing the top 20 % of voxels in healthy controls with the highest feature importance (converted to Z-scores for easier interpretation; image threshold at $Z = 1$). The left panel shows the voxels that best discriminated the *Own* condition from the other two conditions, where red indicates voxels where larger average BOLD activity predicted the *Own* condition, and blue indicates voxels where smaller average BOLD activity predicted the *Own* condition. The right panel shows the same results but for the *Bookstore* condition. **C:** Surface rendering of the top 20 % of voxels contributing most to differentiating the Own condition from each other condition, plotted on the patient's anatomical scan. Red indicates voxels where larger average BOLD activity predicted the *Own* condition and blue indicates where smaller average BOLD activity predicted the *Own* condition.

activity from autobiographical memory regions could decode between the *Bookstore*, *Other* and *Own* conditions (*Mean Balanced Accuracy* = 0.577, $p < .001$). We then tested the model on the patient's data and established that it was able to significantly distinguish between these three conditions (*Balanced Accuracy* = 0.448, $p = .032$) and did so with a balanced accuracy score within the range of healthy controls ($p = .068$; see Fig. 3A).

The model trained on controls used many canonical autobiographical memory regions to help distinguish between the conditions (see Table 1S in the Supplementary Materials for a full list of significant regions). Accurate decoding was primarily driven by voxels within the extrastriate visual cortex, temporal cortex, precuneus, inferior and superior parietal lobule, retrosplenial cortex, parahippocampal gyrus and lateral prefrontal cortex (see Fig. 3B). In general, the model prioritized individual or smaller clusters of voxels within these regions. In the patient, the highest feature importance came from voxels in the extrastriate visual cortex, temporal cortex, superior parietal lobule, lateral prefrontal cortex, and the parahippocampal gyrus (see Fig. 3C and Table 2S in the Supplementary Materials). Recursive feature elimination revealed that the patient's balanced accuracy was maximized when we trained the model with 5 or 10 % of voxels within the autobiographical memory ROI (*Balanced Accuracy* = 0.479; see Fig. 1S in the Supplementary Materials for more details). These models were similarly driven by voxels in the extrastriate visual cortex, temporal cortex, precuneus, posterior cingulate, inferior and superior parietal lobule, retrosplenial cortex, parahippocampal gyrus and lateral prefrontal cortex.

3.2.2. Own vs other

To rule out the possibility that the significant decoding between conditions relied on the visually and experientially dissimilar *Bookstore* condition, we constructed a model that could decode between just the *Own* and *Other* conditions in healthy participants (*Mean Balanced Accuracy* = 0.581, $p < .001$). Once again, this classifier also significantly decoded between these conditions in the patient (*Balanced Accuracy* = 0.609, $p = .032$) and did so well within the range of healthy controls ($p = .620$; see Fig. 4A).

Own vs *Other* decoding was driven by several regions associated with autobiographical memory (see Table 3S for a full list of highly important features). Like the *Bookstore*, *Other* and *Own* comparison, accurate decoding in controls was due to select voxels within the extrastriate visual cortex, temporal cortex, precuneus, posterior cingulate, inferior parietal lobule, retrosplenial cortex, parahippocampal gyrus and lateral prefrontal cortex (see Fig. 4B). In the patient, however, voxels with the highest feature importance were in the extrastriate visual cortex and

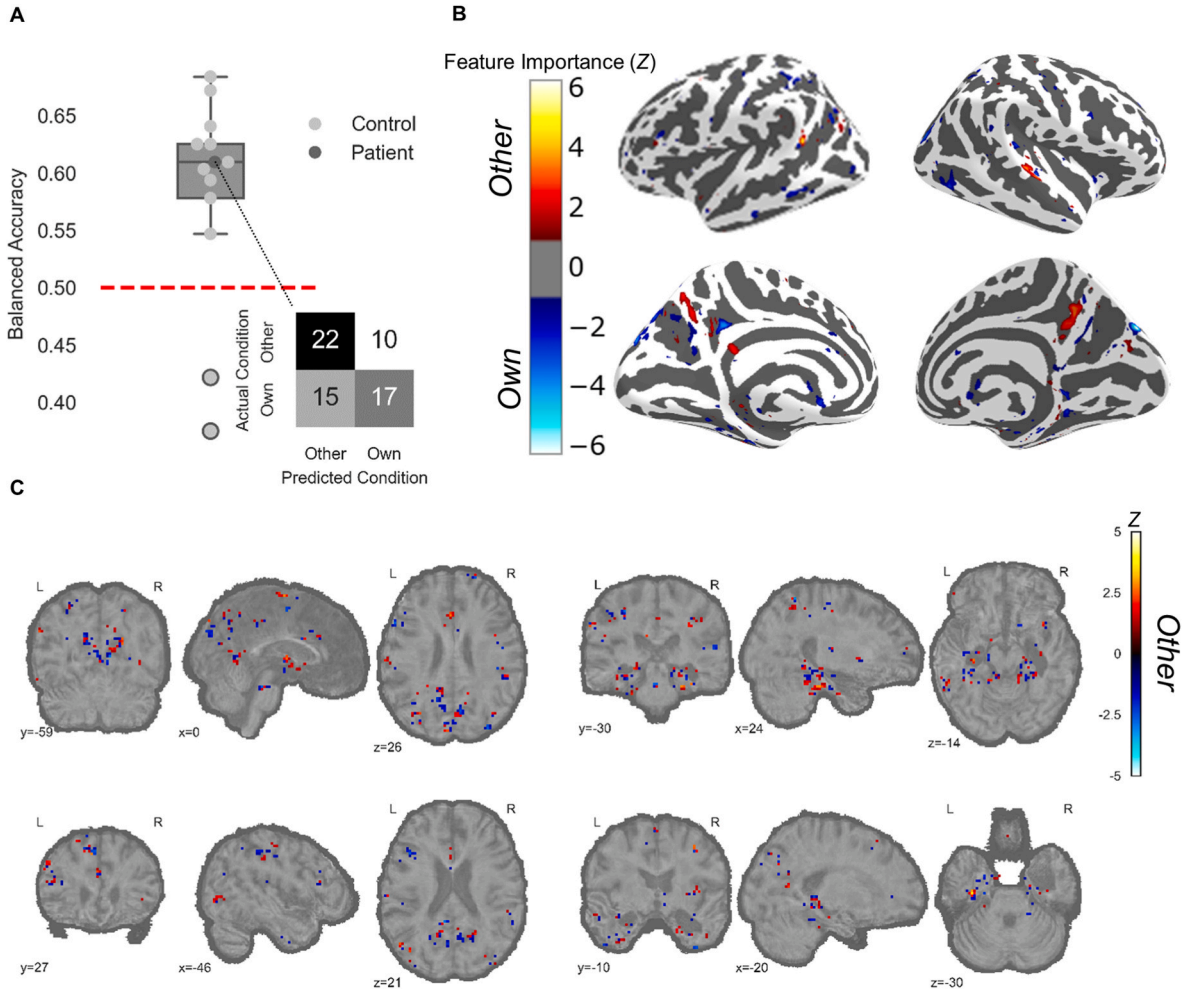

Fig. 4. **A**: A boxplot showing the distribution of balanced accuracy scores across participants when the model decoded between *Own* and *Other* conditions. Individual dots indicate the balanced accuracy of each participant with the dark grey dot reflecting the patient's score. The confusion matrix shows the number of trials in each condition that was predicted by the model (when tested on the patient) and whether that prediction was accurate or inaccurate. **B**: A surface plot showing the top 20 % of voxels in healthy controls with the highest feature importance (converted to Z-scores for easier interpretation; image threshold at Z = 1). Red indicates voxels where larger BOLD activity discriminated the *Other* condition from the *Own* condition and blue indicates the opposite. **C**: A surface plot showing the top 20 % of voxels contributing most to differentiating the *Other* condition from the *Own* condition, plotted on the patient's anatomical scan. Red indicates voxels where larger average BOLD activity predicted the *Other* condition and blue shows where smaller average BOLD activity predicted the *Own* condition

temporal cortex (see Fig. 4C and) Table 4S in the Supplementary Materials. Recursive feature elimination revealed that the model's accuracy when tested on the patient's data was maximized when the model used 5 % of the voxels in the ROI (*Balanced Accuracy* = 0.641). These voxels were distributed across autobiographical memory regions, including the extrastriate visual cortex, temporal cortex, precuneus, posterior cingulate, inferior and superior parietal lobule, retrosplenial cortex, parahippocampal gyrus and lateral prefrontal cortex (see Fig. 1S in the Supplementary Materials for more details).

4. Discussion

4.1. General findings

In this study, we used fMRI to detect neural markers of autobiographical memory in a DoC patient. Through a novel, naturalistic task, we assessed the patient's ability to recollect personal memories from a guided mall visit. By analyzing neural activation restricted to canonical autobiographical memory regions, we successfully differentiated between scenes experienced directly by the patient from highly similar scenes experienced by others. The ability of this patient to perceive and recognize snapshots of their life contrasts sharply with their behavioural profile and diagnosed level of awareness. While preliminary, our findings suggest that clusters of preserved functions critical to identity and meaning-making – such as intact visual processing, self-other discrimination, and the ability to form and recognize new memories – may still be present in this patient.

To the best of our knowledge, this is the first study to experimentally assess autobiographical memory in the absence of reportability in a DoC patient, or indeed, in a non-responsive patient of any kind. Previous studies have only examined autobiographical memory in patients with cognitive motor dissociation under a narrow set of circumstances. These typically involved answering simple yes-or-no questions (e.g., "Do you have a brother?") and responding through specific imagery tasks (e.g., imagining playing tennis for "yes" or walking through their home for "no") (Monti and Owen, 2010). While physical behaviour was not required for these responses to be understood, they were nevertheless "reported", albeit through wilful changes on fMRI activity. In the current study, the preservation of autobiographical retrieval – and, by extension – autobiographical encoding – was inferred from patterns of fMRI activity that were sufficiently similar to those of healthy controls to allow us to draw the strong conclusion that similar cognitive processes were at work.

The only other relevant example is the case report of a patient, presumed to be in a vegetative state, who participated in a research study aimed to assess for awareness and residual cognitive functioning. Remarkably, this patient later recovered and was able to accurately describe specific details about the tasks and even the researchers themselves (Owen, 2017; Taylor et al., 2020). In contrast, our results provide direct neural evidence that the patient in this study – who fluctuated between a diagnosis of vegetative state and minimally conscious state – could recognize experiences from their own life and distinguish them from others. This study introduces an approach that could be used to probe all types of memories in a broad range of behaviourally non-responsive patients and provide new information about the residual cognitive capacities that we typically ascribe to these types of patients. Moreover, the same general approach could also be used to assess the memory capabilities of healthy participants, avoiding the obvious pitfalls associated with active recall, such as misdirection, confusion, or fabrication. Indeed, directly decoding memory content provides an objective means of predicting what a person remembers or does not. This opens up exciting avenues of research, including understanding discrepancies between neural markers of memory and explicit report.

Along similar lines, while our results suggest that key processes of autobiographical memory are preserved in this patient, the quality and quantity of those memories cannot be fully determined. Previous research investigating autobiographical memory in patients with mild, moderate, and severe traumatic brain injury has consistently reported that they have widespread deficits in terms of the quantity of the remembered details and a diminished felt sense of remembering (Baird and Samson, 2014; Knight and O'Hagan, 2009; Lah et al., 2019; Noulhiane et al., 2007; Piolino et al., 2007; Rasmussen et al., 2014; Wammes et al., 2017). Indeed, previous studies have found that even restricted damage to the brain can severely impact episodic memory (Moscovitch et al., 2016; Winocur and Moscovitch, 2011). Of course, while some of these deficits may reflect degraded memory *per se*, others may occur because of collateral damage to the executive functions that organize and coordinate the encoding and retrieval of autobiographical memories. It is in this context that John Duncan's body of work on the role of the multiple demands network becomes very relevant (Duncan, 2010; Duncan and Owen, 2000; Fedorenko et al., 2013). For example, one of the many suggested roles of this network of brain regions is in facilitating the executive control required for successful search and retrieval of autobiographical memories. Notably, voxels in various regions of the multiple demand network regions were influential in decoding between the autobiographical memory conditions in this study; for example, the lateral prefrontal cortex, which has been linked to memory search, retrieval, and the semantic components of autobiographical memory (Cabeza and St Jacques, 2007; Maguire, 2001; Martinelli et al., 2013; Petrides, 2005; Piolino et al., 2007; Steinvorth et al., 2006; Svoboda et al., 2006; see Fig. 2S in the Supplementary Materials for the overlap between the multiple demands network and the autobiographical memory ROI used in this study).

What one might conclude from our results is that autobiographical retrieval was likely very well preserved in our patient and that what we were able to detect was not them experiencing some faint, indistinct, echo of a past experience, but rather a much more elaborated, fully-formed re-experiencing of those recent events, not dissimilar to that experienced by healthy controls when put in exactly the same position. Indeed, the fact that our decoder was able to tell the difference between one person's visit to The Apple Store (or The Bay) and another person's visit to exactly the same Apple Store (or Bay) is quite remarkable because at face value these two experiences were extremely similar. The fact that our model could reliably differentiate between these conditions in our patient, with accuracies within the range of control participants, strongly suggests an autobiographical experience similar to that of healthy participants. Future work will explore this issue further, validating this finding in a larger sample of patients, while further exploring the quality and specificity of these autobiographical memories in patients with DoC.

The regions driving the accurate decoding in this study are consistent with findings from previous autobiographical memory research (Cabeza and St Jacques, 2007; Daviddi et al., 2023; Martinelli et al., 2013; Svoboda et al., 2006). Notably, voxels in the extrastriate visual cortex, temporal cortex, precuneus, inferior and superior parietal lobule, retrosplenial cortex, parahippocampal gyrus and lateral prefrontal cortex were all useful in distinguishing between the autobiographical memory conditions. These regions must act in a coordinated fashion to facilitate the complex set of processes required for autobiographical memory, including search and retrieval, pattern separation, self-referential processing and encoding (Cabeza and St Jacques, 2007; Daviddi et al., 2023; Martinelli et al., 2013; Svoboda et al., 2006). In the patient, the extrastriate visual cortex was particularly important for accurate decoding. Importantly, these visual regions were included in our ROI due to their previously demonstrated role in memory tasks. For example, previous autobiographical memory studies have linked these regions to visual imagery and the re-experiencing of visual memories (Cabeza and St Jacques, 2007).

4.2. Limitations

One potential limitation of this study is that non-memory related confounds may have contributed to the decoder's success in the *Other* vs *Own* comparison. For example, subtle differences in the path taken through the mall or the time of day may have resulted in the patient encountering more people than the healthy controls, or the lighting being different in their videos, potentially changing activity in higher-order visual regions. However, this is unlikely for several reasons. First, we trained the models exclusively on healthy control data, preventing them from learning from idiosyncrasies in the patient's data. Second, we used permutation testing to determine the balanced accuracy expected by chance, accounting for any intrinsic biases in the patient's data. Finally, we manually excluded video clips containing visible participant body parts or other obvious identifiers to minimize the possibility that the machine learning classifier could use these visual features to achieve better performance.

4.3. Conclusion

Our study used a novel naturalistic approach to demonstrate preserved autobiographical memory in a DoC patient showing minimal to no behavioural evidence of awareness. We showed that neuroimaging combined with machine learning was able to detect when autobiographical retrieval has occurred, even in the presence of clips from the same store that were experienced by others. Because autobiographical memory is a cognitive process critical for everyday functioning, conscious awareness, and identity, this finding sheds new light on the covert cognitive capabilities in this group of patients.

CRediT authorship contribution statement

Matthew Kolisnyk: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Geoffrey Laforge:** Writing – review & editing, Writing – original draft, Resources, Project administration, Investigation, Data curation, Conceptualization. **Marie-Ève Gagnon:** Software, Methodology, Investigation, Data curation. **Jonathan Erez:** Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Adrian M. Owen:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to enhance the manuscript's clarity, structure and grammar. After using this tool/service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Declaration of competing interest

The authors have no conflicts to disclose.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuropsychologia.2025.109129.

Data availability

The authors do not have permission to share data.

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