5 Embodied Emotion from Medical Imaging

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**Abstract:** The chapter delves into the profound insights that can be extracted from medical imaging, with a specific focus on CT and MRI data for understanding and identifying emotions. It commences by discussing the potential emotional insights that can be gleaned from these imaging modalities, underlining their significance in the domain of embodied emotion. Subsequently, the chapter explores the intricate process of neuroimaging data preprocessing, an essential step in preparing CT and MRI data for subsequent emotion analysis. Moving forward, it uncovers the emotional patterns hidden within CT and MRI scans, shedding light on how these patterns can be interpreted. Furthermore, the chapter delves into the development of automated emotion detection algorithms tailored for neuroimaging data, substantiating these concepts with compelling case studies and experiments that underscore the practicality and efficacy of this approach.

**Keywords:** CT and MRI Data; Emotional Insights; Neuroimaging Data Preprocessing; Emotional Patterns; Automated Emotion Detection

# 5.1 Introduction

Emotions are not merely abstract states felt within the mind; they are deeply embodied processes rooted in the brain’s structure and function. While psychological theories and behavioural models have long guided our understanding of emotion, modern neuroimaging has ushered in a new era, where emotional states can be visualised, localised, and quantified through high-resolution data captured by medical technologies such as computed tomography (CT) and magnetic resonance imaging (MRI). These imaging modalities provide unprecedented access to the neural substrates of affective experience, offering both structural and functional insights into how emotion is instantiated in the brain's architecture.

Medical imaging connects the subjective experience of emotion with its biological expressions. It enables researchers to observe changes in cortical thickness, subcortical volume, and neural activation patterns that relate to emotional processing, regulation, and memory. Regions such as the amygdala, insula, anterior cingulate cortex, and prefrontal areas are consistently identified across studies as key hubs in the affective brain. These structures do not function in isolation but operate within dynamic, distributed networks that encode valence, arousal, salience, and self-referential processing. Medical imaging has become a crucial tool for mapping these networks, fostering a more detailed understanding of emotion as an embodied, whole-brain phenomenon.

Emotions are not merely abstract psychological states; they are deeply embodied processes anchored in the structural and functional organisation of the brain (Damasio, 2021). Classic psychological models, such as physiological theories and cognitive appraisal frameworks, provide foundational perspectives, but the field has shifted significantly with the advent of high-resolution neuroimaging technologies. Methods such as CT, MRI, functional MRI (fMRI), and diffusion tensor imaging (DTI) allow researchers to visualise, localise, and quantify emotional processes in vivo (Pessoa, 2022; Barrett & Simmons, 2015). These technologies provide structural measures, like cortical thickness and subcortical volume, alongside functional measures of neural activation and connectivity, mapping emotion within its neuroanatomical context.

Medical imaging serves as a bridge between the subjective experience of emotion and its objective biological markers. Consistent evidence points to the amygdala’s role in detecting emotional salience (LeDoux, 2020), the insula’s function in interoceptive awareness and disgust processing (Craig, 2009), the anterior cingulate cortex’s involvement in regulation and conflict monitoring (Etkin et al., 2015), and the prefrontal cortex’s engagement in appraisal and control of emotional states (Ochsner & Gross, 2005; Buhle et al., 2014). These regions do not act in isolation but as parts of large-scale, interconnected networks, such as the salience, default mode, and executive control networks, that encode affective dimensions of valence, arousal, and self-referential meaning (Menon, 2015; Feurer et al., 2021).

Advances in network neuroscience have reframed emotion as an emergent property of dynamic brain systems rather than as a product of static, modular structures. Resting-state fMRI and connectivity analyses reveal that affective states involve constantly shifting patterns of network activity contingent on environmental and bodily inputs (Feurer et al., 2021). Predictive coding theories suggest that the brain integrates sensory and interoceptive signals into top-down expectations, thereby shaping emotional experience in an ongoing loop of prediction and correction (Barrett & Simmons, 2015).

From a translational perspective, neuroimaging not only advances theoretical models but also informs clinical practice. Altered amygdala–prefrontal connectivity has been linked to anxiety disorders (Thomas et al., 2025), while reduced hippocampal volume correlates with depression (Schmaal et al., 2016). Such findings underscore the concept that emotional dysregulation is both a psychological and neurophysiological phenomenon, and highlight the potential of medical imaging to guide neuromodulatory interventions and psychotherapy tailored to individual neurobiological profiles (Koenigs & Grafman, 2009).

Modern neuroimaging positions emotion as a measurable, embodied experience supported by distributed neural networks. This integrative perspective enriches theoretical understanding and strengthens links to applied domains, including mental health treatment and artificial models of affect for psychology-driven AI systems. Beyond basic research, neuroimaging offers critical insights into emotional dysfunction and its neural correlates. In clinical populations, altered patterns in grey matter density or connectivity are often associated with disorders characterised by emotional dysregulation, such as depression, anxiety, post-traumatic stress disorder, and bipolar disorder. The ability to identify these neural markers provides both diagnostic potential and avenues for personalised intervention. Increasingly, researchers are exploring how emotion-specific neural patterns can inform not only treatment but also the prediction of emotional traits and states in healthy individuals.

Beyond basic research, neuroimaging has evolved into a cornerstone methodology for disentangling the complex neural architecture of emotional dysfunction. Its growing role in psychiatry reflects both its capacity to detect subtle circuit-level alterations that precede overt symptom expression and its utility in guiding targeted interventions. Multi-modal imaging approaches, combining structural MRI, functional MRI, diffusion imaging, and emerging neurochemical mapping, reveal patterns of abnormal connectivity and morphology that are remarkably consistent across diagnostic categories, suggesting transdiagnostic signatures of emotional dysregulation (Kaiser et al., 2015; Schmaal et al., 2016).

In major depressive disorder, volumetric reductions in the hippocampus and anterior cingulate cortex, alongside attenuated dorsolateral prefrontal activity, point toward impaired cognitive control over limbic-driven affective responses (Disner et al., 2011). Anxiety disorders, including PTSD, frequently demonstrate hyper-responsivity of the amygdala during threat-related cues and persistent hypoactivity in regulatory prefrontal regions, consistent with a failure to disengage from perceived danger (Etkin & Wager, 2007; Zhu et al., 2012). Bipolar disorder exhibits a more dynamic pattern, with alternations between hyperconnectivity and hypoconnectivity in fronto-limbic circuits depending on mood state (Phillips & Swartz, 2014), reinforcing the view that emotional instability may arise from fluctuating network coordination rather than static structural deficits.

The prognostic potential of these findings lies in their capacity to identify individuals at heightened risk before clinical thresholds are crossed. Longitudinal imaging studies reveal those pre-existing anomalies in prefrontal–amygdala coupling can predict vulnerability to future mood or anxiety episodes, particularly under sustained stress exposure (Morawetz et al., 2017). This predictive dimension is now being operationalised in personalised intervention models, wherein neurobiological markers inform therapy choice, whether through cognitive-behavioural rehearsal targeting regulatory circuits, pharmacological modulation of neurotransmitter balance, or neuromodulatory techniques such as transcranial magnetic stimulation precisely aimed at disrupted cortical nodes.

Furthermore, neuroimaging is beginning to bridge the gap between research in healthy populations and clinical practice. Studies on non-clinical participants show that variations in amygdala–prefrontal dynamics not only correspond to stable emotional traits such as resilience and reactivity but also fluctuate in response to acute training in emotional regulation (Schweizer et al., 2013). Such plasticity underscores a hopeful prospect: that targeted neuromodulation or cognitive training could recalibrate dysfunctional circuits, a concept aligning with the principles of precision psychiatry and preventative mental healthcare (Adrián-Ventura et al., 2021).

In the broader context of affective neuroscience, these converging lines of evidence affirm that emotion is best understood as an emergent property of integrated neural systems, whose disruption manifests in both clinical symptoms and subtle shifts in everyday emotional life. The capacity to map and quantify these systems through neuroimaging not only advances theoretical models of emotion but also lays the foundation for interventions that are both scientifically grounded and individually tailored.As machine learning and computational modelling techniques evolve, CT and MRI data are being repurposed to train algorithms capable of recognising emotion-related brain signatures. These developments hold transformative implications for affective neuroscience and psychoradiology. We are approaching a threshold where it may be possible to infer emotional states not from self-report or observation, but from high-dimensional imaging data alone. Such progress raises not only technical but also philosophical and ethical questions: To what extent can emotion be reduced to a neural footprint? What does it mean for emotion to be legible to machines? The convergence of structural neuroanatomy, functional brain dynamics, and computational analysis offers a compelling lens through which to re-examine the nature of affect, not just as a psychological construct but as a measurable, embodied phenomenon etched into the architecture of the brain, consistent with the broader PsAIchology framing of integrating AI and psychological science (Farahani et al., 2024).

# 5.2 Emotional Insights from CT and MRI Data

Advancements in neuroimaging have fundamentally shifted the landscape of emotion research by rendering emotional processes visible, quantifiable, and spatially mappable within the human brain. Among the most powerful tools for this exploration are CT and MRI, both of which allow researchers to investigate the structural and functional substrates of affect. These technologies have enabled a growing body of work that treats emotion not merely as a psychological or behavioural output but as a biologically embodied phenomenon with distinct neural signatures. While CT imaging offers valuable information about brain structure, particularly in clinical populations where lesions or trauma may affect emotional regulation, MRI provides a more nuanced view into the dynamic, interconnected networks that support emotional processing in real time.

The ability to observe emotion-related brain activity has opened up new theoretical possibilities for understanding how emotions stem from the interaction of several neural systems. Instead of being confined to separate modules, current research indicates that emotional states emerge from networked interactions across cortical and subcortical regions. Studies using functional MRI (fMRI) have consistently highlighted areas such as the amygdala, insula, ventromedial prefrontal cortex (vmPFC), and anterior cingulate cortex (ACC) as involved in emotional reactivity, interoceptive awareness, and regulation (Craig, 2002, 2009; Etkin, Büchel, & Gross, 2015; Hiser & Koenigs, 2018; Phelps & LeDoux, 2005). These regions work together to produce affective responses that are appropriate to the context and socially adaptive, emphasising the embodied and integrative character of emotion. For example, the amygdala’s well-established role in fear detection and salience encoding is now understood to operate not in isolation but in reciprocal dialogue with the prefrontal cortex, which influences and interprets affective signals based on cognitive and social considerations (Etkin et al., 2015; Hiser & Koenigs, 2018; Phelps & LeDoux, 2005).

Structural MRI (sMRI) studies have further revealed that individual differences in emotional traits, such as trait anxiety, affective empathy, or emotional reactivity, are associated with measurable differences in brain morphology. Variations in grey matter volume or cortical thickness in emotion-relevant regions have been linked to stable patterns of emotional functioning. For example, increased volume in the anterior insula has been correlated with greater emotional awareness and empathy, while reductions in dorsolateral prefrontal cortex thickness are often observed in individuals with difficulties in emotion regulation or depression (van Dam et al., 2021). These findings contribute to a neuroanatomical grounding of emotional capacities, suggesting that the way individuals experience and manage their emotions is partly a function of their neural architecture.

CT imaging, although more limited in resolution compared to MRI, has been essential in revealing how structural brain abnormalities affect affective function, particularly in neurological injury. In cohorts with traumatic brain injury (TBI) and stroke, voxel-based lesion–symptom mapping has linked damage to the orbitofrontal and adjacent ventral prefrontal regions with behavioural disinhibition and socio-emotional disturbance, consistent with classic OFC roles in affective regulation (Knutson et al., 2015; Gläscher et al., 2012). For white-matter pathways, damage to the right uncinate fasciculus selectively impairs emotional empathy, highlighting tract-level influences on affective integration (Oishi et al., 2015; Herbet et al., 2015). In clinical pipelines, CT volumes are often co-registered to MRI-based or CT templates to improve normalisation for group analyses. This is an established practice facilitated by age-appropriate templates and toolboxes (Rorden et al., 2012).

Beyond structural findings, the real strength of MRI lies in its ability to capture the functional dynamics of emotional states as they unfold. Functional MRI studies using emotionally evocative tasks, such as viewing facial expressions, listening to emotionally charged sounds, or recalling autobiographical memories, have mapped activation patterns that correspond not only to general emotion categories (e.g., fear, joy) but also to specific dimensions of affect such as arousal and valence. These studies consistently report distinct yet overlapping activation clusters, suggesting that the brain represents emotions in a distributed and context-sensitive manner rather than through fixed, modular circuits. In particular, high arousal states tend to engage the anterior insula and amygdala more robustly, while positively valenced experiences show increased connectivity between the ventral striatum and medial prefrontal areas (Lindquist et al., 2012).

Moreover, the use of **resting-state functional connectivity** has opened a new frontier in understanding the intrinsic architecture of the emotional brain. Researchers have begun to identify specific resting-state networks, such as the default mode network (DMN), salience network (SN), and central executive network (CEN), that exhibit characteristic patterns of connectivity associated with baseline emotional traits. Increased coupling between the amygdala and DMN, for example, has been linked to rumination and negative affect. At the same time, stronger connectivity between the CEN and the vmPFC correlates with better emotion regulation capacity. These resting-state findings emphasise the continuity between emotional traits and moment-to-moment emotional states, reinforcing the view that emotion is deeply embedded in the brain’s baseline functional architecture (Kleckner et al., 2017).

Importantly, neuroimaging is beginning to bridge the gap between **subjective affective experience** and **objective neural data**. Using multivariate pattern analysis (MVPA), researchers can now classify emotional states based on distributed patterns of fMRI activity with increasing accuracy. These patterns extend across cortical and subcortical regions, suggesting that emotion is encoded through large-scale population codes rather than isolated loci. Some researchers have even proposed the existence of neural *signatures* for basic emotions. These are multiregional activation patterns that reliably predict states like sadness or fear across individuals and tasks. Although the universality and specificity of such signatures remain under debate, their emergence underscores the growing sophistication of MRI-based emotion decoding (Kragel & LaBar, 2015; Chang et al., 2015; Saarimäki et al., 2016; Zhou et al., 2021).

The integration of diffusion tensor imaging (DTI) has further expanded the anatomical resolution of emotion research. By mapping white-matter pathways, DTI reveals how information flows between regions involved in emotional generation and regulation. Integrity of the uncinate fasciculus, which connects the anterior temporal lobe/amygdala with orbitofrontal–vmPFC circuits, has been linked to individual differences in emotion regulation, emotional sensitivity, and related affective traits (Xu et al., 2022; Tromp et al., 2019; Xu et al., 2023; see also Granger et al., 2021). Such findings support the view that emotions depend on efficient communication between emotional and executive systems, not solely on isolated cortical loci.

As the field advances, a key question remains: to what extent can emotional profiles be inferred or predicted from neuroimaging data? While the current consensus is that such predictions are probabilistic and context-dependent, there is growing optimism that with the appropriate combination of anatomical, functional, and connectivity data, it may be possible to construct comprehensive neural models of emotion that reflect both transient states and enduring traits. These models hold promise not only for scientific understanding but also for clinical applications, such as early detection of affective disorders, personalised treatment planning, and the development of neurofeedback interventions based on real-time emotion tracking.

Taken together, CT and MRI have become indispensable tools for exploring the neural embodiment of emotion. They provide a means of anchoring affective experience within the biological substrate of the brain, offering insights that are at once structural, functional, and dynamic. As these technologies continue to evolve, their integration with computational modelling, artificial intelligence, and behavioural science will deepen our understanding of the emotional brain as a distributed system whose architecture both reflects and shapes the feelings we call our own.

# 5.3 Neuroimaging Data Preprocessing: Preparing CT and MRI Data for Emotion Analysis

The translation of raw neuroimaging data into meaningful emotional insights hinges on a meticulous and scientifically rigorous preprocessing pipeline. In studies of embodied emotion, where the goal is to identify subtle structural and functional correlates of affect, preprocessing is not merely a technical preamble but a foundational step that ensures both the validity and reproducibility of the findings. Whether derived from CT or MRI, neuroimaging data are subject to numerous sources of noise, artefact, and individual anatomical variability that must be accounted for before emotion-related analysis can proceed.

In the case of MRI, preprocessing typically begins with anatomical alignment and head motion correction. Even minimal head movements can distort voxel-based representations of emotional activation, leading to spurious findings or reduced statistical power. Algorithms such as FSL’s MCFLIRT (Smith et al., 2004) or SPM’s realignment module (Ashburner et al., 2014) are widely used to estimate and correct for motion by aligning each volume to a reference image. Motion artefacts are particularly problematic in emotional tasks, where stimuli may trigger involuntary reactions like facial expressions or body shifts. Therefore, studies involving affective elicitation often include motion parameters as covariates in subsequent statistical models to isolate genuine emotional activation from movement-induced signal changes (Esteban et al., 2019).

To screen for frame-wise intensity changes driven by head motion or rapid physiological shifts, we inspect temporal Derivative VARiance across voxels (DVARS). DVARS highlights sudden global changes in the BOLD volume from one frame to the next; large spikes are typical markers of motion or slice-to-slice corruption. DVARS are in Python, created as:

from nilearn.maskers import NiftiMasker

from nilearn import image

import numpy as np, matplotlib.pyplot as plt

bold = image.load\_img("your.nii.gz")

masker = NiftiMasker(standardize=False, detrend=False).fit(bold)

X = masker.transform(bold) # shape: (n\_scans, n\_voxels)

dX = np.diff(X, axis=0)

dvars = np.sqrt((dX\*\*2).mean(axis=1)) \* 1000 # scale for visibility

m, s = dvars.mean(), dvars.std()

plt.figure(figsize=(16,4))

plt.plot(dvars); plt.axhline(m+2\*s, color='orange', ls='--')

plt.axhline(m+3\*s, color='red', ls='--')

plt.xlabel("Frame"); plt.ylabel("DVARS (a.u.)"); plt.title("DVARS (frame-wise)")

plt.tight\_layout()

For our example shown in Figure 1, a single, pronounced spike aligns with the only obvious artefactual dip in the global signal. A clear outlier is visible around frame ~176 (dashed lines show mean+2SD and mean+3SD alert levels). This simple check tells us where censoring or nuisance modelling (e.g., motion regressors) may be needed before any statistical analysis.

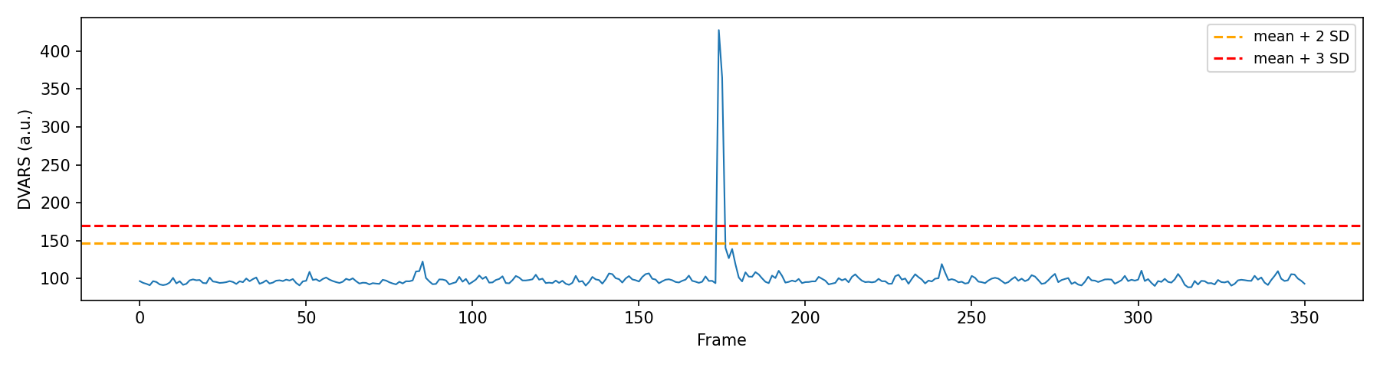


Figure 1. DVARS time-series

Alongside DVARS, we track the global mean signal as the average BOLD intensity inside the brain at each frame. This complements DVARS by showing slow drifts and abrupt drops on an absolute scale. In the same run, the global signal exhibits a single sharp deflection at the same time index as the DVARS spike, strengthening the case for targeted scrubbing or modelling of that frame and its neighbours. Python code for the global mean signal is:

bold = image.load\_img("your.nii.gz")

masker = NiftiMasker(standardize=False, detrend=True).fit(bold)

X = masker.transform(bold) # (n\_scans, n\_voxels)

global\_ts = X.mean(axis=1)

plt.figure(figsize=(16,4))

plt.plot(global\_ts); plt.xlabel("Frame"); plt.ylabel("Global mean signal (a.u.)")

plt.title("Global mean fMRI signal"); plt.tight\_layout()

The output of the previous code is shown in Figure 2. The deep transient around frame ~176 mirrors the DVARS spike and is highly suggestive of head movement or brief acquisition instability.

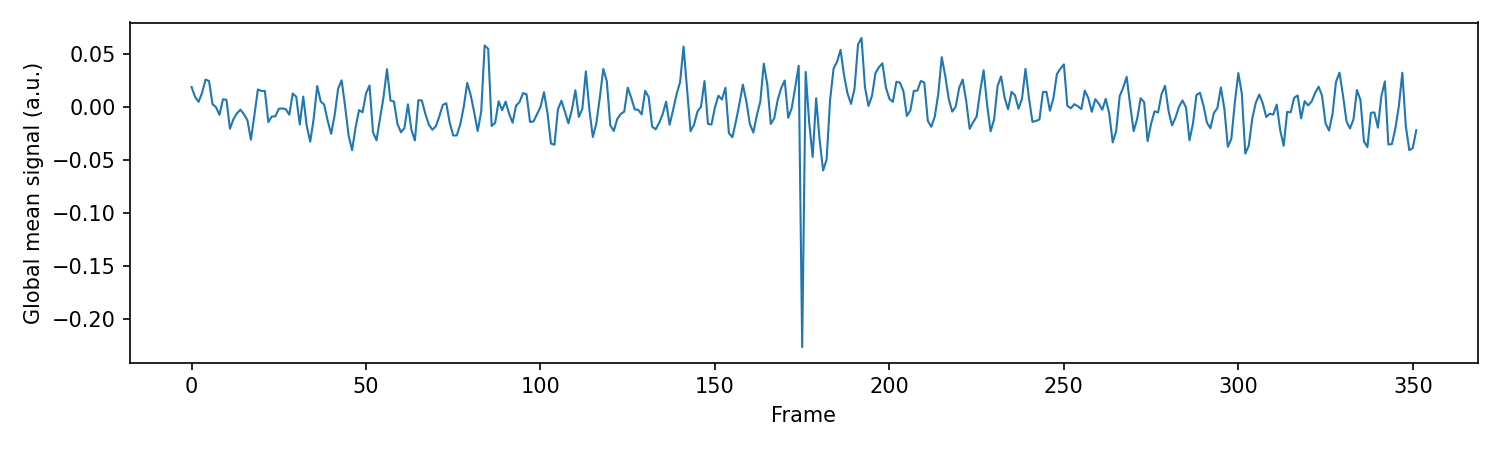


Figure 2. Global mean fMRI signal across time

Following motion correction, anatomical normalisation ensures that each participant’s brain is spatially aligned to a common reference template, such as the Montreal Neurological Institute Template-MNI152 (Fonov et al., 2011) or Talairach space (Collins et al., 1994). This step allows for group-level comparisons and voxel-wise analysis by transforming individual datasets into a shared neuroanatomical space. However, in emotion research, especially when exploring subcortical structures like the amygdala or hippocampus, misalignment during normalisation can blur the signal and reduce the specificity of regional findings. As such, high-resolution templates and nonlinear warping algorithms, such as those provided by ANTs (Madge, 2020), are often employed to preserve anatomical detail. Manual inspection and quality control are also essential to verify the fidelity of spatial normalisation, particularly when working with clinical or pediatric populations where brain morphology may deviate from standard templates.

Before coregistration and tissue segmentation, it helps to illustrate how common filters change anatomical contrast. The panel in Figure 3 compares a raw T1-weighted slice with Gaussian smoothing and edge-enhancing operators (Sobel, Frangi, Laplacian). Only modest smoothing is used in typical workflows; stronger edge filters are *diagnostic* visuals here, not steps we apply to the anatomical pipeline. Showing them reminds the reader why over-filtering can exaggerate edges and mislead registration or segmentation.

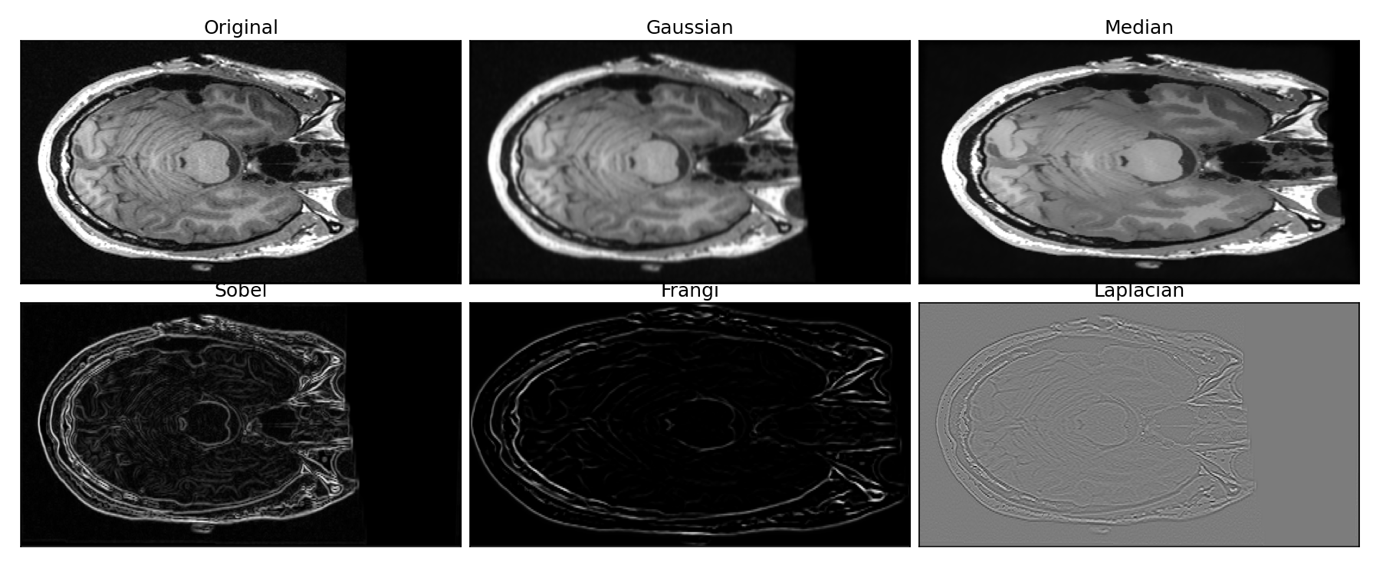


Figure 3. Effect of basic filters on the middle axial slice of T1w

To produce the panel from Figure 3, we can use this code:

t1w = image.load\_img("your.nii.gz")

sl = image.index\_img(t1w, None).get\_fdata()[:,:,t1w.shape[2]//2]

sl = (sl - np.percentile(sl,2)) / (np.percentile(sl,98)-np.percentile(sl,2)+1e-9)

panels = {

"Original": sl, "Gaussian": gaussian\_filter(sl,1),

"Median": gaussian\_filter(sl,0.01), "Sobel": sobel(sl),

"Frangi": frangi(sl), "Laplacian": laplace(sl)

}

fig, axes = plt.subplots(2,3,figsize=(12,7))

for ax,(k,v) in zip(axes.ravel(), panels.items()): ax.imshow(v,cmap='gray'); ax.set\_title(k); ax.axis('off')

fig.tight\_layout()

For functional MRI data, preprocessing continues with slice timing correction and spatial smoothing. Because different slices of the brain are acquired at slightly different times during each repetition time (TR), slice timing correction adjusts the data to a common temporal reference. While its necessity depends on the acquisition protocol (e.g., whether multi-band acceleration was used), the inclusion of this step is generally recommended in event-related emotional tasks to improve the temporal alignment of stimulus responses. Spatial smoothing, on the other hand, enhances signal-to-noise ratio by averaging voxel intensities within a defined kernel, typically around 6–8 mm of full-width half-maximum. Though this step can obscure fine-grained patterns, it increases the sensitivity to detect broader regional activation and compensates for inter-individual anatomical variability (Poldrack et al., 2020).

When decoding or classifying emotions, extra preprocessing steps are often used to prepare data for machine learning pipelines. These include temporal filtering to remove low-frequency drifts, z-scoring to standardise voxel intensities, and extracting region-of-interest (ROI) time series for feature creation. In studies aiming to predict emotional valence or arousal from fMRI data, denoising techniques such as Independent Component Analysis (ICA) based artefact removal (e.g., ICA-AROMA) and physiological noise correction (e.g., RETROICOR) are used to ensure predictions are not influenced by non-neural sources. The growing use of MVPA and deep learning in emotion research highlights the importance of careful preprocessing, as even small inconsistencies can reduce model generalisability and interpretability.

We summarise temporal reliability with **tSNR = mean / SD** of the BOLD signal at each voxel. High tSNR implies stable time series and greater sensitivity to detect task-evoked changes; low tSNR flags susceptibility or motion-sensitive regions (e.g., orbitofrontal cortex, anterior temporal lobes). The tSNR map (Figure 4) shows broadly good coverage with expected drops near sinuses and inferior temporal regions. Warm colours indicate higher temporal stability, while cooler areas flag regions where effects may be harder to detect.

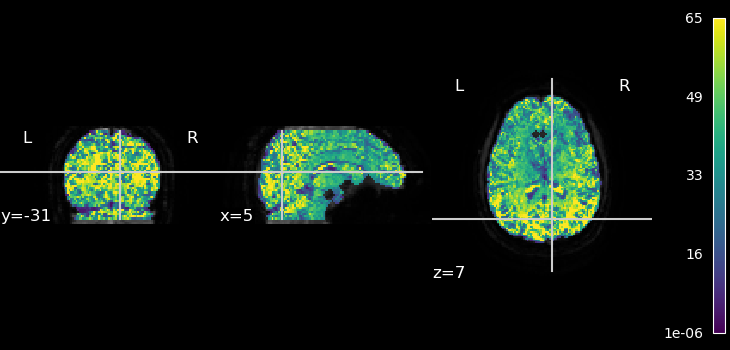


Figure 4. tSNR (mean/SD) over the run

A **tSNR histogram** in Figure 5 complements the map by showing the overall quality of the run. Here, most brain voxels cluster around ~35–55, with a long upper tail. Such distributions are typical for 3 T fMRI at 2–3 mm isotropic resolution. If the bulk of voxels fell below ~20–25, we’d anticipate reduced sensitivity and would consider stricter denoising, more aggressive censoring, or excluding the run. Peak around ~40–50 suggests adequate data quality for first-level GLM in this subject.

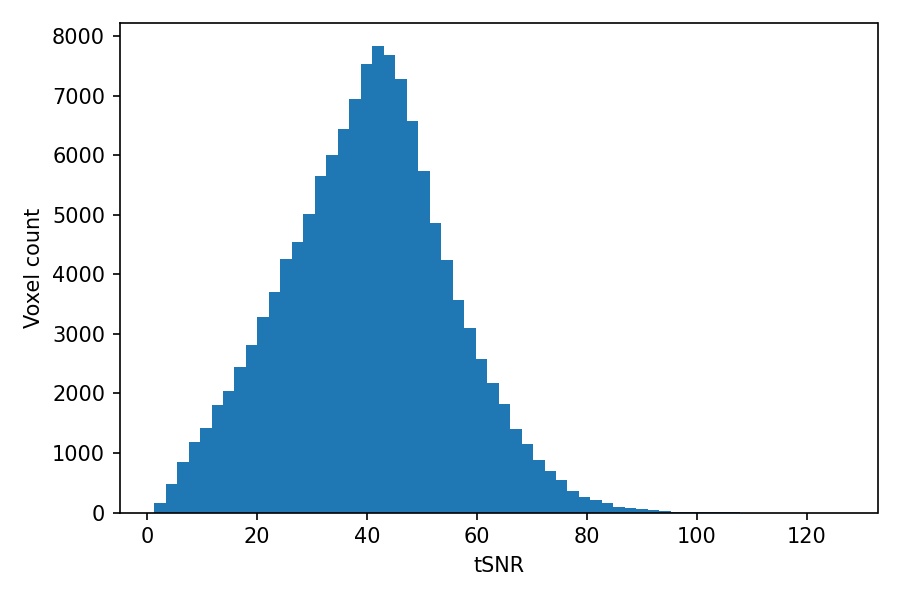


Figure 5. Distribution of within-brain tSNR values

Preprocessing of **structural MRI** data also involves several important steps. For grey matter morphometry analyses, tools like FreeSurfer (Fischl, 2012) and CAT12 are used to segment the brain into tissue classes (grey matter, white matter, cerebrospinal fluid), extract cortical thickness measures, and compute surface-based metrics such as gyrification and curvature. These morphological features are then statistically compared across individuals with different emotional profiles, such as high versus low trait anxiety or emotion dysregulation. Accurate segmentation is crucial, especially in emotion-relevant regions that have complex folding patterns or diverse tissue properties. Visual inspection of segmentations and following standardised preprocessing pipelines are essential to ensure reliability, particularly when analysing small subcortical structures that play significant roles in emotional processing.

When working with CT data, preprocessing tends to be more constrained due to lower spatial resolution and the absence of functional contrast. In clinical and lesion–symptom mapping studies, CT lesion masks are routinely normalised or co-registered to common MRI templates to facilitate group localisation and statistical mapping (Bates et al., 2003; Karnath et al., 2004; Rorden et al., 2012). Practical pipelines apply skull stripping and lesion segmentation to enhance anatomical clarity before analysis (Hu et al., 2023; Muschelli et al., 2015; Najm et al., 2019). Although MRI is generally more sensitive than CT for subtle pathology such as diffuse axonal injury and microstructural white-matter damage, CT remains valuable where MRI is unavailable or contraindicated and as part of retrospective cohorts (Dabas et al., 2024; Shenton et al., 2012; Vo et al., 2022).

Cross-modal preprocessing, which combines CT, structural MRI, functional MRI, and even DTI, is gaining popularity in integrative models of emotion. These pipelines involve advanced coregistration and fusion techniques to align datasets with differing resolutions and contrasts. When analysing emotional processing across modalities, preserving anatomical congruence is critical. For example, the structural connectivity derived from DTI must align precisely with the functional activations from fMRI to assess emotion-related network dynamics. Fusion methods such as joint independent component analysis (jICA) or canonical correlation analysis (CCA) are increasingly used to identify shared components across modalities that track with emotional traits or responses.

An emerging trend in neuroimaging preprocessing is the shift toward **automated, reproducible workflows** that combine best practices with open-source accessibility. Pipelines such as fMRIPrep (Esteban et al., 2019), MRIQC (Esteban et al., 2017), and Nipype (Gorgolewski et al., 2011) enable researchers to preprocess large datasets with minimal manual intervention while maintaining consistency and transparency. In emotion research, where data are often collected across multiple sessions, tasks, or sites, such standardised workflows are essential for harmonisation and scalability. The availability of Brain Imaging Data Structure (BIDS) formatting further facilitates dataset sharing and reuse, accelerating progress toward large-scale models of embodied emotion (Gorgolewski et al., 2016).

While preprocessing may appear as a technical backdrop to the more conceptual work of emotion analysis, it is, in fact, one of the most consequential stages in determining the success and credibility of neuroimaging-based emotion research. Errors or inconsistencies introduced at this stage can propagate through to final interpretations, potentially leading to invalid conclusions about the neural bases of affect. Conversely, careful, validated preprocessing unlocks the full potential of neuroimaging to reveal the embodied architecture of emotional life, setting the stage for accurate modelling, meaningful prediction, and responsible application.

# 5.4 Revealing Emotional Patterns in CT and MRI Scans

The growing convergence between affective neuroscience and neuroimaging has brought to light a critical realisation: emotional experiences are not abstract psychological states detached from the body but are physically encoded across multiple levels of brain architecture. As CT and MRI technologies become increasingly refined, they allow researchers to move beyond localisation of emotional processes and instead focus on identifying and characterising patterns with distributed, reproducible, and functionally meaningful configurations of neural activation, morphology, and connectivity that reflect the embodied nature of emotion. These patterns form the neurobiological substrate upon which subjective feeling states emerge and fluctuate, offering measurable indices of emotional function and dysfunction.

MRI, with its ability to capture both structural and functional information, has played a central role in this effort. fMRI studies often begin by isolating ROIs known to be involved in emotional processing, such as the amygdala, anterior insula, vmPFC, and ACC, and examining how these regions activate in response to emotional stimuli or tasks. However, more recent work has shown that single-region analyses are insufficient to capture the full complexity of emotional states. Emotional experiences are dynamic, multicomponent phenomena involving sensory processing, autonomic feedback, cognitive interpretation, and motor preparation. Therefore, researchers have turned to MVPA, dynamic causal modelling (DCM), and graph theoretical approaches to detect **distributed emotional patterns** that span across brain systems and time.

For example, studies using emotional film clips, facial expression tasks, or autobiographical memory recall have consistently revealed that specific emotional categories, such as fear, happiness, disgust, or sadness, are associated with unique but overlapping patterns of activation. Rather than being localised, these patterns typically involve synchronised activity across limbic regions, sensory cortices, and default mode network hubs. A fear-related pattern, for instance, may involve co-activation of the amygdala, periaqueductal grey, and right anterior insula, combined with suppression in the medial prefrontal cortex. In contrast, sadness may show stronger engagement of the subgenual ACC, posterior cingulate cortex, and precuneus, suggesting greater involvement of self-referential processing (Kragel & LaBar, 2016).

Such findings are strengthened by **pattern classification algorithms**, which can learn to distinguish emotional states based on fMRI voxel-level data. These classifiers, often employing support vector machines or neural networks, are trained on labelled data to predict unseen emotional states from brain activation patterns. The success of these models demonstrates that emotional information is not just detectable but **decodable** within neuroimaging data (Pereira et al., 2009; Haynes, 2015; Norman et al., 2006; Kragel & LaBar, 2015; Chang et al., 2015). This ability to infer emotional states from brain data opens new frontiers for emotion tracking in real time, particularly in clinical populations where self-report may be unreliable.

MRI-based structural analyses have also uncovered persistent morphological patterns linked to emotional traits and tendencies. Voxel-based morphometry and cortical-thickness studies consistently associate regional brain anatomy with affective capacities. Regarding empathy, structural differences commonly found in the anterior insula and inferior frontal gyrus (IFG) reflect individual variability. Grey-matter measures in the anterior insula correlate with trait empathy, while IFG morphology also varies with affective-empathy scores (Mutschler et al., 2013; Banissy et al., 2012). In mood and personality disorders, major depressive disorder shows significant hippocampal volume reductions, especially with early onset and recurrent episodes, along with widespread but modest cortical thinning, including prefrontal regions (Schmaal et al., 2016; Schmaal et al., 2017). Borderline personality disorder literature reports changes in limbic volumes (e.g., amygdala/hippocampus) and decreased prefrontal cortical thickness in several samples, consistent with impaired top-down regulation (Nunes et al., 2009; Giannoulis et al., 2025; Rossi et al., 2015).

These anatomical patterns are not static. Longitudinal imaging studies have documented **neuroplastic changes** in emotion-related structures in response to therapeutic interventions such as mindfulness training, cognitive-behavioural therapy, or pharmacological treatment. For example, patients with depression often show increases in hippocampal volume following successful treatment, while the normalisation of hyperactive amygdala responses to negative stimuli has been observed with exposure therapy in anxiety disorders. Such findings point to the potential of structural and functional patterns to serve not just as markers of emotional states but as **biomarkers of emotional change**.

CT is generally less sensitive than MRI for subtle lesions, but it can still be useful in lesion–symptom mapping pipelines; converging work shows orbitofrontal/anterior temporal damage and disruption of fronto-limbic white-matter tracts are linked to emotional flattening, disinhibition, and impaired social–affective judgment (Bechara, Damasio, & Damasio, 2000; Koenigs & Tranel, 2007; Hiser & Koenigs, 2018; Operskalski, Paul, Colom, Barbey, & Grafman, 2015). For sensitivity, MRI (including diffusion methods) consistently outperforms CT for many fine-grained pathologies (e.g., diffuse axonal injury, white-matter disease), but CT can complement MRI when triangulating structure–function relationships.

One promising development involves **connectivity-based pattern analysis**, where researchers examine how emotional experiences are shaped by communication between brain regions rather than isolated activity. Using DTI, which traces white matter tracts, and resting-state fMRI, researchers can construct emotional connectivity profiles for individuals. High emotional granularity is the ability to distinguish and label subtle emotional states. It has been linked to increased connectivity between the prefrontal cortex and the insula, suggesting enhanced top-down modulation of interoceptive signals. Conversely, emotional rigidity or impulsivity has been associated with stronger amygdala-subcortical coupling and reduced connectivity with regulatory cortical regions (Fan et al., 2016).

Recent innovations have pushed these analyses even further by employing **deep learning models** to automatically extract emotional features from imaging data. These models can identify latent representations of affect that are not easily visible through standard statistical techniques. For instance, convolutional neural networks (CNNs) trained on MRI slices have been used to predict anxiety or depression severity with considerable accuracy. While still in early stages, such approaches hold the potential to uncover hidden emotional patterns embedded in high-dimensional brain data, enabling more personalised and precise emotion science. Related machine-learning frameworks have also been applied to affect-linked constructs beyond core emotions, such as love addiction, where features and explanations clarify predictive factors (Farahani et al., 2025).

As researchers continue to refine these techniques, the goal is not merely to map emotion onto the brain but to understand the **embodied logic of affective experience**. Emotional patterns in neuroimaging data are shaped by a complex interplay of structural predispositions, situational demands, and internal states. They vary across individuals, evolve across time, and reflect both the universality and the individuality of emotional life. CT and MRI thus serve as more than diagnostic tools. They are **windows into the embodied architecture of human feeling**, offering a rare and powerful glimpse into the neural choreography of the emotional self.

# 5.5 Towards Automated Emotion Detection: Algorithms and Neuroimaging

The increasing convergence of neuroscience, artificial intelligence, and affective computing has paved the way for automated systems capable of detecting emotional states directly from neuroimaging data. With the rapid expansion of data availability and algorithmic sophistication, the field is witnessing a shift from descriptive and correlational brain-emotion studies toward predictive and diagnostic frameworks that leverage machine learning to decode emotion from MRI and CT scans. In this landscape, Python has emerged as the dominant programming language, enabling the integration of neuroimaging preprocessing tools, machine learning frameworks, and statistical modelling into unified, replicable pipelines (Kovač et al., 2024). This section explores the design and implementation of automated emotion detection systems based on neuroimaging, with an emphasis on Python-based practices and the role of computational models in transforming raw brain data into affective insights.

At the core of automated emotion detection is the representation of high-dimensional neuroimaging data in a form that is amenable to algorithmic learning. For MRI, this often involves voxel-wise data from functional scans or morphological features such as cortical thickness and regional volumes from structural scans. In Python, such features are typically extracted using libraries like nibabel, nilearn, or PySurfer, which provide interfaces to load, visualise, and manipulate neuroimaging data in NIfTI format. Once the imaging features are prepared, they can be combined with behavioural or physiological labels, such as emotion ratings or arousal indices, to form supervised datasets for model training.

The most common approach to emotion decoding involves the use of **machine learning classifiers** trained to predict discrete emotions (e.g., fear, happiness) or continuous affective dimensions (e.g., valence, arousal) from imaging data. Python’s scikit-learn library offers a robust suite of algorithms for this purpose, including support vector machines (SVMs), random forests, and logistic regression, all of which have been widely applied in neuroimaging research. For example, a basic pipeline might include loading preprocessed fMRI activation maps, flattening voxel data into 1D feature vectors, and training an SVM to distinguish between high- and low-arousal states:

from sklearn.svm import SVC

from sklearn.model\_selection import cross\_val\_score

from sklearn.preprocessing import StandardScaler

import numpy as np

# X: fMRI data (n\_samples x n\_voxels), y: arousal labels

scaler = StandardScaler()

X\_scaled = scaler.fit\_transform(X)

clf = SVC(kernel='linear', C=1)

scores = cross\_val\_score(clf, X\_scaled, y, cv=5)

print(f"Mean classification accuracy: {np.mean(scores):.2f}")

This type of approach allows for the rapid evaluation of model performance across individuals, tasks, or emotional conditions. With proper validation and regularisation, it is possible to interpret model weights and identify the most predictive brain regions associated with emotional states, resulting in predictive and neuroscientific insight. Comparable supervised pipelines are also used in psychological health domains, for example the classification of chronic pain outcomes (Kovač et al., 2025). A complementary line of work uses calibrated regression to predict internal shame, with XGBoost performing best and distress tolerance emerging as the strongest predictor (Kovač, Ratković, Farahani, & Watson, 2025b).

In recent years, emotion detection has moved beyond classical machine learning toward **deep learning**, particularly when working with raw or minimally preprocessed imaging data (Avberšek et al., 2022). CNNs have been adapted to handle three-dimensional (3D) MRI volumes, allowing models to learn spatial features directly from imaging slices or volumes without the need for manual feature engineering. Python frameworks such as PyTorch and TensorFlow facilitate the development of these models, offering modules for 3D convolutions, data augmentation, and graphics processing unit acceleration. For instance, a simplified version of a 3D CNN for binary emotion classification might look like:

import torch

import torch.nn as nn

class Emotion3DCNN(nn.Module):

def \_\_init\_\_(self):

super(Emotion3DCNN, self).\_\_init\_\_()

self.conv1 = nn.Conv3d(1, 16, kernel\_size=3)

self.pool = nn.MaxPool3d(2)

self.fc1 = nn.Linear(16 \* 13 \* 13 \* 13, 2) # Adjust dimensions based on input shape

def forward(self, x):

x = self.pool(torch.relu(self.conv1(x)))

x = x.view(-1, 16 \* 13 \* 13 \* 13)

x = self.fc1(x)

return x

Such models have been used to classify emotional traits from structural MRI, detect affective disorders, or predict momentary affect from task-based fMRI. However, they require large datasets and careful regularisation to avoid overfitting. This represents a challenge given the limited sample sizes common in neuroimaging studies.

To address this, researchers have adopted **transfer learning** and **feature selection** strategies. For example, models pre-trained on large datasets like UK Biobank or the Human Connectome Project can be fine-tuned on smaller emotion-labelled datasets, improving performance and stability. Additionally, dimensionality reduction techniques like principal component analysis (PCA) or feature importance ranking (e.g., using sklearn.feature\_selection.SelectKBest) are often used to reduce computational load and focus learning on the most informative regions.

Another important development is the application of **multimodal fusion** (He et al., 2020), where structural, functional, and diffusion data are integrated into unified models. Python-based pipelines using packages like MNE-Python, dipy, and nilearn allow for preprocessing and aligning different modalities. These fused models can capture more complex emotional dynamics. For instance, they are combining structural connectivity from DTI with task-based fMRI activation to predict how individuals will respond emotionally to a stressor or social cue.

Automated emotion detection systems have also begun to incorporate **temporal dynamics**, especially in studies using naturalistic stimuli such as movies, narratives, or social interactions. Recurrent neural networks (RNNs) and transformers have been used to model how emotional responses evolve, based on dynamic fluctuations in brain activity. The PyTorch library, in particular, provides flexible modules for constructing such models, enabling time series classification and prediction from BOLD signal trajectories.

The ethical implications of automated emotion detection from brain data must also be acknowledged. While these systems offer the potential for emotion-aware technologies, personalised medicine, and affective monitoring, they raise questions about privacy, consent, and the interpretability of predictions. Misclassification of emotional states, especially in sensitive contexts like mental health or judicial settings, can have serious consequences. Therefore, the deployment of such systems requires rigorous validation, transparent reporting of limitations, and ethical safeguards that prioritise user autonomy and well-being.

Looking ahead, one of the most promising directions involves **real-time emotion decoding** using fMRI neurofeedback. In these setups, brain activity is analysed in real time to provide participants with feedback on their current emotional state, allowing them to learn to self-regulate affect through neural training. Python scripts leveraging NiTime, NeuroFeedback Suite, or real-time data streaming APIs are central to implementing these feedback loops. The combination of online detection and adaptive feedback introduces an entirely new interactive, embodied, and computationally mediated paradigm for emotion research.

Automated emotion detection from neuroimaging is thus not a distant aspiration but an increasingly operational reality. Python-based tools and algorithms offer a powerful foundation for this work, enabling reproducible, scalable, and interpretable systems that can decode the emotional self from the architecture and activity of the brain. As techniques continue to mature, these systems will play a critical role in reshaping how we understand, measure, and intervene in the emotional dimensions of human experience.

# 5.6 Case Studies and Experiments

To bridge the technical sophistication of neuroimaging-based emotion detection with practical application, this section presents an illustrative case study and simulated experiments that demonstrate how CT and MRI data can be harnessed, analysed, and interpreted in the context of emotion research. These examples are especially designed for readers who may not have a deep background in neuroimaging or machine learning but wish to understand how the integration of these tools reveals embodied emotional processes.

We analyse a public dataset **ds000201** from **OpenNeuro** (Nilsonne et al., 2018). The dataset is organised in BIDS format and includes multiple participants (e.g., sub-9001, sub-9002, …), often with two sessions each (ses-1, ses-2). For each session, there is:

* a functional BOLD run named task-arrows (EPI time series), and
* a high-resolution T1-weighted anatomical image.

Each functional run is accompanied by an events.tsv file containing, at minimum, onset, duration, and trial\_type per event. In this dataset, the events also include additional columns (e.g., *event\_type*, *cue\_to\_participant*, *stimulus\_type*, *time\_until\_response*, and *rated\_success\_of\_regulation*). These reveal that participants viewed emotional pictures (e.g., IAPS images) and were periodically cued (e.g., “Maintain”) on how to respond, making it an emotion-related task. To keep this case study focused and fully reproducible, we present a **single-subject** analysis (sub-9001, ses-1). The same steps apply to any subject/session pair. Keep in mind that you don’t need to load the entire dataset, especially since these datasets may be very memory-intensive. A single subject can already demonstrate how emotion-related signals are modelled and interpreted.

Before any brain map is created, the timing of the task is turned into predictors in a **design matrix** (see Figure 6). Think of it as the storyboard of the experiment, frame by frame. Each column is a regressor (e.g., the task condition and slow *drift* terms that remove scanner trends); each row corresponds to one time point (one fMRI volume).

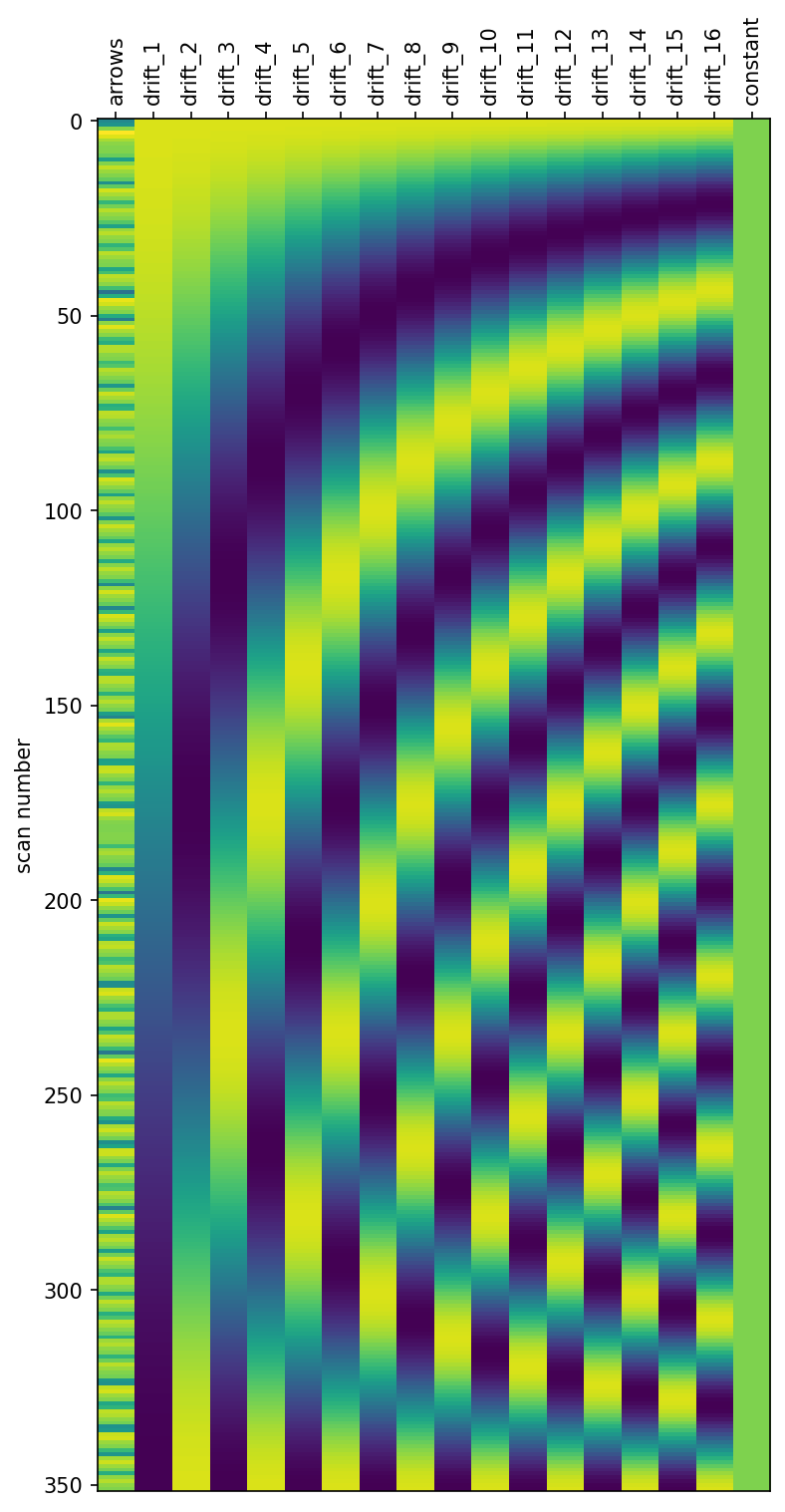


Figure 6. Design matrix for sub-9001/ses-1

The leftmost column labelled **arrows** encodes when task events occurred (convolved with a hemodynamic response model so it matches brain physiology). The remaining columns (drift\_1…drift\_16 and constant) capture slow scanner drifts and the baseline. Figure 6 shows the *inputs* to the statistical model. A clear design matrix ensures we can later claim that *activity increased during the task* rather than inadvertently modelling artefacts or idle periods. If the colours look like waves, that’s expected. Those sinusoid-like *drift* columns remove slow fluctuations unrelated to emotion processing.

Before zooming into slices, we first show a *glass-brain* overview (Figure 7) of the whole z-map to give the reader an immediate sense of where the task leaves its footprint. This global view is helpful for non-technical readers: it reveals that effects are distributed across the cortex and not confined to a single spot, and it lets us check symmetry and gross alignment without committing to a specific slice. The unthresholded z-map for Task > baseline is projected through the brain in four canonical views (left sagittal, coronal, right sagittal, axial). Brighter voxels indicate stronger |z|. This *X-ray-style* view is ideal for a fast global orientation before we pick exact slices.

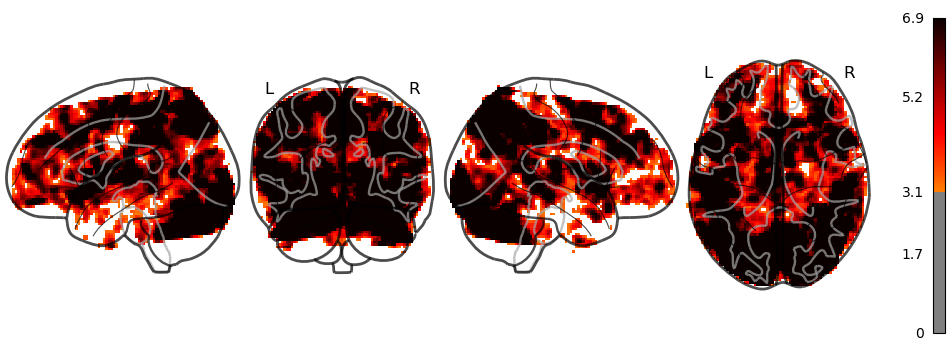


Figure 7. Glass-brain overview (MNI152 space, affine-aligned)

With the design matrix in place, we fit a **first-level** general linear model (GLM) to estimate where the BOLD signal increased or decreased during the task relative to the implicit baseline. We use a canonical hemodynamic response and standard nuisance terms (cosine drifts; AR(1) noise model). The result is a **z-map**: higher values mean a stronger task effect. We present the **unthresholded** statistical map in a slice series. Showing the continuous z-values before applying any threshold helps readers grasp the full spatial pattern (including subtle, subthreshold structure) and prevents the impression that activation is *all-or-nothing*. From inferior to superior, Figure 8 shows continuous effect sizes rather than a hard cutoff. This makes bilateral patterns and gradual changes with z-position visible and prepares the reader for the thresholded view that follows.

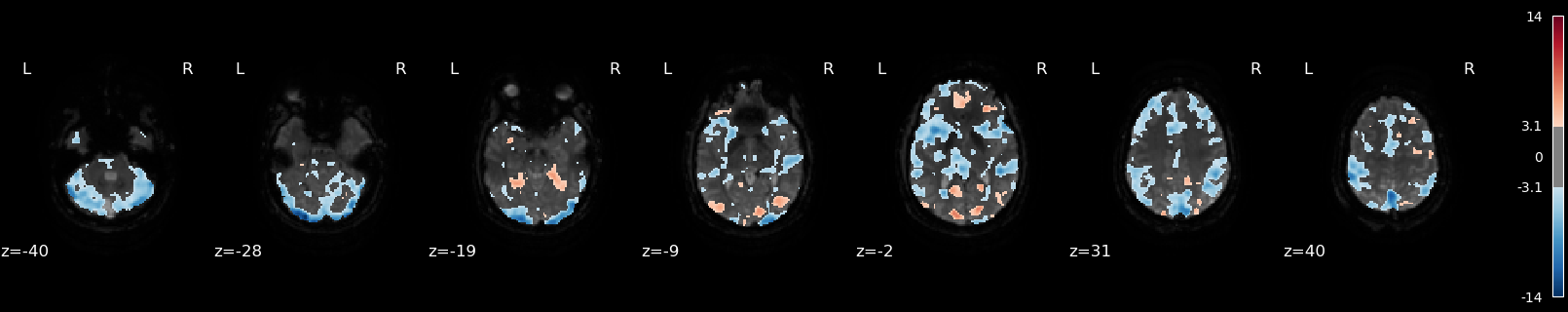


Figure 8. Axial slice series (unthresholded z for Task > baseline)

To anchor the effect in 3D coordinates, we add an unthresholded orthogonal cut (Figure 9) with crosshairs. This answers the practical question of *where the peak is* before we move to a cleaned, thresholded display. Sagittal, coronal, and axial planes with crosshairs provide world-coordinate context for the strongest cluster. Using the continuous map here avoids hiding near-threshold structure.

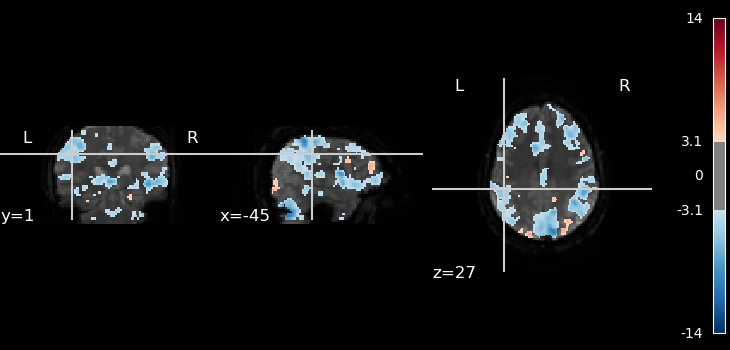


Figure 9. Orthogonal cuts (unthresholded z for Task > baseline)

Having oriented the reader with unthresholded views, we now apply a conventional cluster-forming display threshold of |z| > 3.1 (see Figures 10 and 11). The thresholded maps simplify interpretation for reports and tables while preserving the bilateral, fronto-parietal pattern seen above.

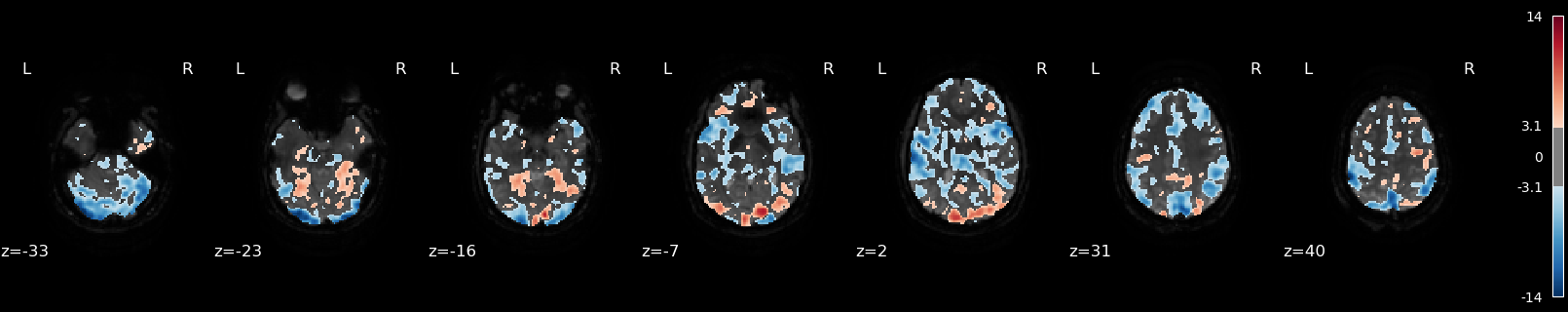


Figure 10. Task > baseline, axial cut-series, |z|>3.1

Multiple axial slices (bottom of the brain to the top) in Figure 10 show clusters where the task significantly modulated activity. Warm colours (red) indicate positive z-scores (activation > baseline), while cool colours (blue) indicate negative z-scores (deactivation < baseline). A slice-series makes spatial patterns easy to spot (e.g., bilateral, posterior, or frontal effects) without getting lost in a single 3-D view.

Orthogonal cuts shown in Figure 11 (sagittal, coronal, axial) with crosshairs provide world coordinates of the peak shown. Readers often want to know where exactly a strong effect lies. This view provides precise coordinates for reporting or ROI definition. We use a two-tailed display (|z|>3.1), so both positive and negative effects are visible. This is why the colorbar ranges from negative to positive values. A negative value does *not* mean *bad*. It rather simply indicates a lower BOLD signal than baseline in that region during the task period.

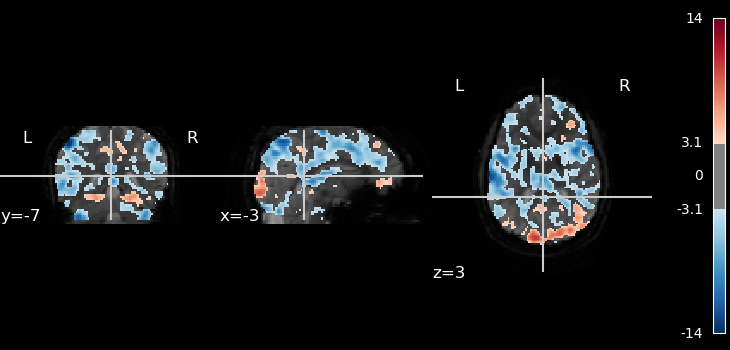


Figure 11. Task > baseline, orthogonal views, |z|>3.1

Group templates are convenient, but many readers understand the anatomy best when effects are shown on the person’s own T1 image.

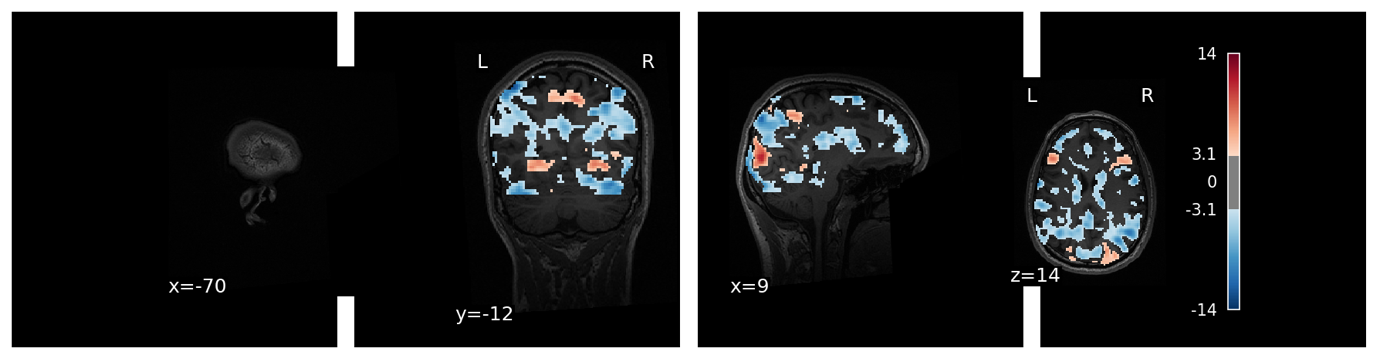


Figure 12. Task > baseline, overlaid on the subject’s T1

Three orthogonal mosaics show how the thresholded z-map sits on the participant’s high-resolution anatomy. It reassures the reader that the activations are not abstract blobs. They align with recognisable anatomical landmarks in this individual.

Emotion research often highlights the amygdala and vmPFC. To make the results accessible, we extract the mean z-value from small, predefined ROIs and present them as simple bars with a 95% bootstrap band in Figure 13. These summaries are not formal hypothesis tests here. They’re intuitive summaries that help non-specialists relate the map to familiar emotion-related loci.

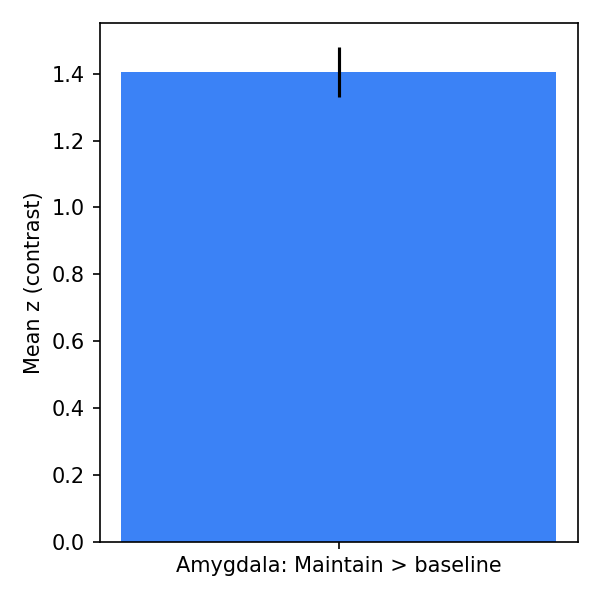


Figure 13. ROI summary: Amygdala, mean z for Task > baseline

The bar shows the mean effect within a bilateral amygdala ROI. The thin line marks a 95% bootstrap interval around the mean.For emotion tasks that involve viewing affective images, amygdala engagement is a common expectation. A positive mean suggests the task period coincides with increased signal in this region (in this subject).

vmPFC is another canonical node in affect and regulation (Figure 14). Here, the mean is close to zero with a wide uncertainty band. Not all emotion-linked regions *light up* in every subject or task. Showing both amygdala and vmPFC side-by-side prevents cherry-picking and teaches that individual datasets differ.

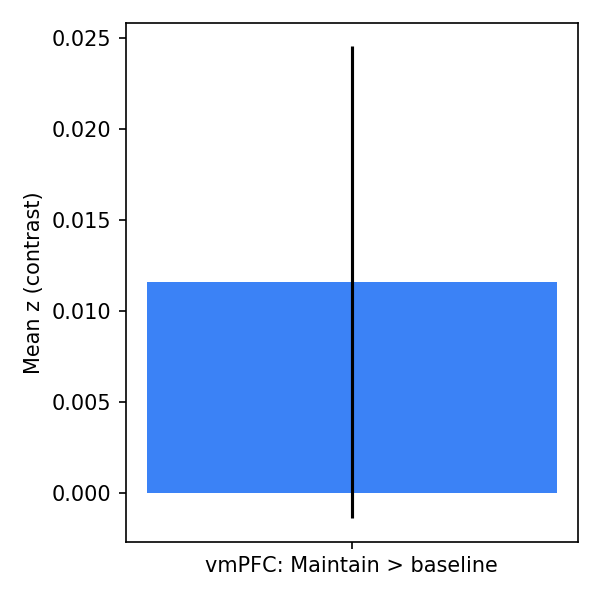
****

Figure 14. ROI summary: vmPFC, mean z for Task > baseline

We will now demonstrate how we computed ROI bars in Python. Define a small spherical ROI (e.g., radius 6 mm) using MNI coordinates or load a standard atlas mask; then average the GLM z-map within that ROI:

from nilearn.maskers import NiftiSpheresMasker

from nilearn import image

zmap\_img = image.load\_img("your.nii.gz") # your GLM contrast

# Example: left & right amygdala centers (approx MNI); replace with your own

amygdala\_seeds = [(-22, -4, -16), (22, -4, -16)]

masker = NiftiSpheresMasker(seeds=amygdala\_seeds, radius=6, standardize=False)

roi\_vals = masker.fit\_transform(zmap\_img).ravel() # average across seeds

mean = roi\_vals.mean()

Beyond *where is stronger*, readers often ask how regions interact. A psychophysiological interaction (PPI) analysis probes whether the coupling between a seed region (here, amygdala) and the rest of the brain changes with the psychological context (the task events). We illustrate this with a single uncorrected exploratory map shown in Figure 15.

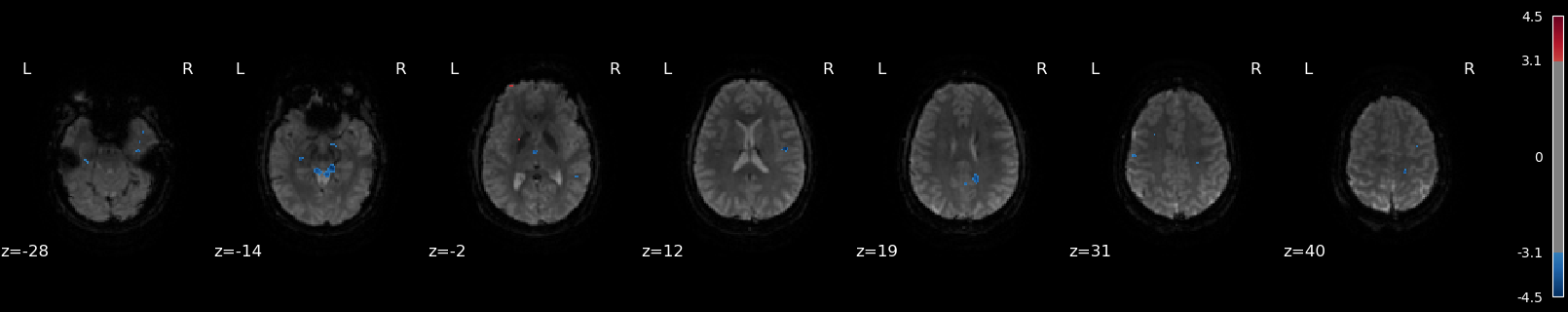


Figure 15. PPI map: Amygdala × task, thresholded

The blue points in Figure 15 indicate voxels where coupling with the amygdala is weaker during the task. Warm tones (if present) would indicate stronger coupling. Figure 15 introduces the idea that emotion is not just about local activation but also about network dynamics. For a single subject, this is illustrative; group-level replication is required for firm conclusions. PPI is sensitive to how we model events and noise. Treat single-subject PPI displays as *hypothesis-generating*, not as definitive evidence.

Readers who prepare reports often need a table of peaks and cluster sizes. We exported peaks above |z|>3.1 with a minimal extent (e.g., k ≥ 10 voxels). We are showing only the first 8 rows in Table 1:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Cluster ID | X | Y | Z | Peak Stat | Cluster Size (mm3) |
| 1 | 5.61499786 | -49.843994 | -14.32048 | 11.993052 | 35285 |
| 1a | 13.1149979 | -44.218994 | -2.3204727 | 11.6147929 |  |
| 1b | 24.3649979 | -34.843994 | -11.920479 | 11.4090705 |  |
| 1c | -9.3850021 | -51.718994 | -2.3204727 | 10.632828 |  |
| 2 | -33.760002 | -40.468994 | -11.920479 | 9.77413744 | 3265 |
| 2a | -46.885002 | -38.593994 | -2.3204727 | 5.86542419 |  |
| 2b | -50.635002 | -31.093994 | -7.1204758 | 3.55650637 |  |
| 2c | -41.260002 | -31.093994 | 2.47953033 | 3.26262283 |  |

Table 1. Peak/cluster summary, |z|>3.1, k≥10

Columns include: Cluster ID (with sub-peaks 1a, 1b, …), MNI X/Y/Z (mm), Peak Stat (z-value), and Cluster Size (mm³ for the main peak). The sign of Peak Stat indicates the direction (positive = activation; negative = deactivation). The Figure 12 colorbar shows both positive and negative ranges, as we used a two-tailed display. That’s why you’ll see negative values in figures even though the table caption says *z>3.1*. However, our Table 1 records |z|>3.1 (absolute value).

This single-subject case study demonstrates the complete path from task design to statistical maps, from maps to interpretable summaries, and from local activation to context-dependent interactions. The visual strategy (design matrix → glass-brain (global) → unthresholded slices → unthresholded ortho → thresholded axial/ortho → subject-space overlay → ROI bars → PPI → peak table) lets non-technical readers follow the logic without wrestling with code. We see how an emotion-evoking task leaves a measurable footprint in the brain and how that footprint can be explained clearly, reproducibly, and responsibly. This case study illustrates the full arc of neuroimaging-based emotion research using tools that are increasingly open, intuitive, and replicable. While the technical foundations are complex, the insights they generate can be visualised, explained, and appreciated even by those with limited programming or neuroscience expertise.

By embedding emotion in visible, measurable brain patterns, we foster a deeper public and scientific understanding of how the brain embodies emotional life. The integration of real-time monitoring, predictive modelling, and visually intuitive platforms promises a future in which neuroscience is not just the domain of specialists but a source of emotional self-understanding, clinical insight, and human connection.

**References:**

Adrián-Ventura, J., Costumero, V., Parcet, M. A., & Ávila, C. (2019). Linking personality and brain anatomy: a structural MRI approach to Reinforcement Sensitivity Theory. *Social cognitive and affective neuroscience*, *14*(3), 329-338.

Ashburner, J., Barnes, G., Chen, C. C., Daunizeau, J., Flandin, G., Friston, K., ... & Penny, W. (2014). SPM12 manual. *Wellcome Trust Centre for Neuroimaging, London, UK*, *2464*(4), 53.

Avberšek, L. K., & Repovš, G. (2022). Deep learning in neuroimaging data analysis: Applications, challenges, and solutions. *Frontiers in neuroimaging*, *1*, 981642.

Banissy, M. J., Kanai, R., Walsh, V., & Rees, G. (2012). Inter-individual differences in empathy are reflected in human brain structure. *Neuroimage*, *62*(3), 2034-2039.

Barrett, L. F., & Simmons, W. K. (2015). Interoceptive predictions in the brain. *Nature reviews neuroscience*, *16*(7), 419-429.

Bates, E., Wilson, S. M., Saygin, A. P., Dick, F., Sereno, M. I., Knight, R. T., & Dronkers, N. F. (2003). Voxel-based lesion–symptom mapping. *Nature neuroscience*, *6*(5), 448-450.

Bechara, A., Damasio, H., & Damasio, A. R. (2000). Emotion, decision making and the orbitofrontal cortex. *Cerebral cortex*, *10*(3), 295-307.

Buhle, J. T., Silvers, J. A., Wager, T. D., Lopez, R., Onyemekwu, C., Kober, H., ... & Ochsner, K. N. (2014). Cognitive reappraisal of emotion: a meta-analysis of human neuroimaging studies. *Cerebral cortex*, *24*(11), 2981-2990.

Chang, L. J., Gianaros, P. J., Manuck, S. B., Krishnan, A., & Wager, T. D. (2015). A sensitive and specific neural signature for picture-induced negative affect. *PLoS biology*, *13*(6), e1002180.

Collins, D. L., Neelin, P., Peters, T. M., & Evans, A. C. (1994). Automatic 3D intersubject registration of MR volumetric data in standardized Talairach space. *Journal of computer assisted tomography*, *18*(2), 192-205.

Craig, A. D. (2002). How do you feel? Interoception: the sense of the physiological condition of the body. *Nature reviews neuroscience*, *3*(8), 655-666.

Craig, A. D. (2009). How do you feel—now? The anterior insula and human awareness. *Nature reviews neuroscience*, *10*(1), 59-70.

Dabas, M. M., Alameri, A. D., Mohamed, N. M., Mahmood, R., Kim, D. H., Samreen, M., ... & Khan, S. (2024). Comparative efficacy of MRI and CT in traumatic brain injury: A systematic review. *Cureus*, *16*(10).

Damasio, A. (2021). *Feeling & knowing: Making minds conscious*. Pantheon.

Disner, S. G., Beevers, C. G., Haigh, E. A., & Beck, A. T. (2011). Neural mechanisms of the cognitive model of depression. *Nature Reviews Neuroscience*, *12*(8), 467-477.

Esteban, O., Birman, D., Schaer, M., Koyejo, O. O., Poldrack, R. A., & Gorgolewski, K. J. (2017). MRIQC: Advancing the automatic prediction of image quality in MRI from unseen sites. *PloS one*, *12*(9), e0184661.

Esteban, O., Markiewicz, C. J., Blair, R. W., Moodie, C. A., Isik, A. I., Erramuzpe, A., ... & Gorgolewski, K. J. (2019). fMRIPrep: a robust preprocessing pipeline for functional MRI. *Nature methods*, *16*(1), 111-116.

Etkin, A., & Wager, T. D. (2007). Functional neuroimaging of anxiety: a meta-analysis of emotional processing in PTSD, social anxiety disorder, and specific phobia. *American journal of Psychiatry*, *164*(10), 1476-1488.

Etkin, A., Büchel, C., & Gross, J. J. (2015). The neural bases of emotion regulation. *Nature reviews neuroscience*, *16*(11), 693-700.

Fan, L., Li, H., Zhuo, J., Zhang, Y., Wang, J., Chen, L., ... & Jiang, T. (2016). The human brainnetome atlas: a new brain atlas based on connectional architecture. *Cerebral cortex*, *26*(8), 3508-3526.

Farahani, H., Watson, P., Bezan, T., Kovač, N., Winter, L. C., Blagojević, M., ... & Jiménez, P. (2024). PsAIchology: An Intelligent Direction in Psychological Sciences. In *10th International Scientific Conference Technics, Informatics and Education-TIE 2024*. Faculty of Technical Sciences Čačak, University of Kragujevac.

Farahani, H., Watson, P., Kovač, N., Sheykhangafshe, F. B., Azadfallah, P., Allahyari, A., ... & Chesli, R. R. (2025). Unraveling the Complexity of Love Addiction Using Machine Learning Algorithms: The Influence of Positive and Negative Affect, Interpersonal Needs, and Self-Hate. In *International Handbook of Love: Transcultural and Transdisciplinary Perspectives* (pp. 1-22). Cham: Springer Nature Switzerland.

Feurer, C., Jimmy, J., Chang, F., Langenecker, S. A., Phan, K. L., Ajilore, O., & Klumpp, H. (2021). Resting state functional connectivity correlates of rumination and worry in internalizing psychopathologies. *Depression and Anxiety*, *38*(5), 488-497.

Fischl, B. (2012). FreeSurfer. *Neuroimage*, *62*(2), 774-781.

Fonov, V., Evans, A. C., Botteron, K., Almli, C. R., McKinstry, R. C., Collins, D. L., & Brain Development Cooperative Group. (2011). Unbiased average age-appropriate atlases for pediatric studies. *Neuroimage*, *54*(1), 313-327.

Giannoulis, E., Nousis, C., Sula, I. J., Georgitsi, M. E., & Malogiannis, I. (2025). Understanding the Borderline Brain: A Review of Neurobiological Findings in Borderline Personality Disorder (BPD). *Biomedicines*, *13*(7), 1783.

Gläscher, J., Adolphs, R., Damasio, H., Bechara, A., Rudrauf, D., Calamia, M., ... & Tranel, D. (2012). Lesion mapping of cognitive control and value-based decision making in the prefrontal cortex. *Proceedings of the National Academy of Sciences*, *109*(36), 14681-14686.

Gorgolewski, K. J., Auer, T., Calhoun, V. D., Craddock, R. C., Das, S., Duff, E. P., ... & Poldrack, R. A. (2016). The brain imaging data structure, a format for organizing and describing outputs of neuroimaging experiments. *Scientific data*, *3*(1), 1-9.

Gorgolewski, K., Burns, C. D., Madison, C., Clark, D., Halchenko, Y. O., Waskom, M. L., & Ghosh, S. S. (2011). Nipype: a flexible, lightweight and extensible neuroimaging data processing framework in python. Frontiers in neuroinformatics, 5, 13.

Granger, S. J., Leal, S. L., Larson, M. S., Janecek, J. T., McMillan, L., Stern, H., & Yassa, M. A. (2021). Integrity of the uncinate fasciculus is associated with emotional pattern separation-related fMRI signals in the hippocampal dentate and CA3. *Neurobiology of Learning and Memory*, *177*, 107359.

Haynes, J. D. (2015). A primer on pattern-based approaches to fMRI: principles, pitfalls, and perspectives. *Neuron*, *87*(2), 257-270.

He, Z., Li, Z., Yang, F., Wang, L., Li, J., Zhou, C., & Pan, J. (2020). Advances in multimodal emotion recognition based on brain–computer interfaces. *Brain sciences*, *10*(10), 687.

Herbet, G., Lafargue, G., Moritz-Gasser, S., de Champfleur, N. M., Costi, E., Bonnetblanc, F., & Duffau, H. (2015). A disconnection account of subjective empathy impairments in diffuse low-grade glioma patients. *Neuropsychologia*, *70*, 165-176.

Hiser, J., & Koenigs, M. (2018). The multifaceted role of the ventromedial prefrontal cortex in emotion, decision making, social cognition, and psychopathology. *Biological psychiatry*, *83*(8), 638-647.

Hu, D., Liang, H., Qu, S., Han, C., & Jiang, Y. (2023). A fast and accurate brain extraction method for CT head images. *BMC Medical Imaging*, *23*(1), 124.

Kaiser, R. H., Andrews-Hanna, J. R., Wager, T. D., & Pizzagalli, D. A. (2015). Large-scale network dysfunction in major depressive disorder: a meta-analysis of resting-state functional connectivity. *JAMA psychiatry*, *72*(6), 603-611.

Karnath, H. O., Fruhmann Berger, M., Zopf, R., & Küker, W. (2004). Using SPM normalization for lesion analysis in spatial neglect. *Brain*, *127*(4), e10-e10.

Kleckner, I. R., Zhang, J., Touroutoglou, A., Chanes, L., Xia, C., Simmons, W. K., ... & Feldman Barrett, L. (2017). Evidence for a large-scale brain system supporting allostasis and interoception in humans. *Nature human behaviour*, *1*(5), 0069.

Knutson, K. M., Dal Monte, O., Schintu, S., Wassermann, E. M., Raymont, V., Grafman, J., & Krueger, F. (2015). Areas of brain damage underlying increased reports of behavioral disinhibition. *The Journal of neuropsychiatry and clinical neurosciences*, *27*(3), 193-198.

Koenigs, M., & Grafman, J. (2009). The functional neuroanatomy of depression: distinct roles for ventromedial and dorsolateral prefrontal cortex. *Behavioural brain research*, *201*(2), 239-243.

Koenigs, M., & Tranel, D. (2007). Irrational economic decision-making after ventromedial prefrontal damage: evidence from the Ultimatum Game. *Journal of Neuroscience*, *27*(4), 951-956.

Kovač, N., Ratković, K., Farahani, H., & Watson, P. (2024). A practical applications guide to machine learning regression models in psychology with Python. *Methods in Psychology*, *11*, 100156.

Kovač, N., Ratković, K., Farahani, H., & Watson, P. (2025b). Machine learning regression models for internal shame. Acta Psychologica, 260, 105721.

Kovač, N., Ratković, K., Watson, P., Farahani, H., & Bagheri Sheykhangafshe, F. (2025). Machine learning classification models for predicting chronic pain. *Current Psychology*, 1-14.

Kragel, P. A., & LaBar, K. S. (2015). Multivariate neural biomarkers of emotional states are categorically distinct. *Social cognitive and affective neuroscience*, *10*(11), 1437-1448.

Kragel, P. A., & LaBar, K. S. (2016). Decoding the nature of emotion in the brain. *Trends in cognitive sciences*, *20*(6), 444-455.

LeDoux, J. (2020). *The deep history of ourselves: The four-billion-year story of how we got conscious brains*. Penguin.

Lindquist, K. A., Wager, T. D., Kober, H., Bliss-Moreau, E., & Barrett, L. F. (2012). The brain basis of emotion: a meta-analytic review. *Behavioral and brain sciences*, *35*(3), 121-143.

Madge, V. (2020). *Evaluating Voxelmorph: a learning-based 3D non-linear registration algorithm, against the non-linear symmetric normalization technique from ANTs*. McGill University (Canada).

Menon, V., & Toga, A. W. (2015). Brain mapping: An encyclopedic reference. *Academic Press: Cambridge, MA, USA*, 597-611.

Morawetz, C., Bode, S., Baudewig, J., & Heekeren, H. R. (2017). Effective amygdala-prefrontal connectivity predicts individual differences in successful emotion regulation. *Social cognitive and affective neuroscience*, *12*(4), 569-585.

Muschelli, J., Ullman, N. L., Mould, W. A., Vespa, P., Hanley, D. F., & Crainiceanu, C. M. (2015). Validated automatic brain extraction of head CT images. *Neuroimage*, *114*, 379-385.

Mutschler, I., Reinbold, C., Wankerl, J., Seifritz, E., & Ball, T. (2013). Structural basis of empathy and the domain general region in the anterior insular cortex. *Frontiers in human neuroscience*, *7*, 177.

Najm, M., Kuang, H., Federico, A., Jogiat, U., Goyal, M., Hill, M. D., ... & Qiu, W. (2019). Automated brain extraction from head CT and CTA images using convex optimization with shape propagation. *Computer Methods and Programs in Biomedicine*, *176*, 1-8.

Nilsonne, G., Tamm, S., d’Onofrio, P., Thuné, H. Å., Schwarz, J., Lavebratt, C., Liu, J. J., Månsson, K. N. T., Sundelin, T., Axelsson, J., Fransson, P., Kecklund, G., Fischer, H., Lekander, M., & Åkerstedt, T. (2018). *ds000201* (Version R1.0.5) [Data set]. OpenNeuro.

Norman, K. A., Polyn, S. M., Detre, G. J., & Haxby, J. V. (2006). Beyond mind-reading: multi-voxel pattern analysis of fMRI data. *Trends in cognitive sciences*, *10*(9), 424-430.

Nunes, P. M., Wenzel, A., Borges, K. T., Porto, C. R., Caminha, R. M., & De Oliveira, I. R. (2009). Volumes of the hippocampus and amygdala in patients with borderline personality disorder: a meta-analysis. *Journal of personality disorders*, *23*(4), 333-345.

Ochsner, K. N., & Gross, J. J. (2005). The cognitive control of emotion. *Trends in cognitive sciences*, *9*(5), 242-249.

Oishi, K., Faria, A. V., Hsu, J., Tippett, D., Mori, S., & Hillis, A. E. (2015). Critical role of the right uncinate fasciculus in emotional empathy. *Annals of neurology*, *77*(1), 68-74.

Operskalski, J. T., Paul, E. J., Colom, R., Barbey, A. K., & Grafman, J. (2015). Lesion mapping the four-factor structure of emotional intelligence. *Frontiers in human neuroscience*, *9*, 649.

Pereira, F., Mitchell, T., & Botvinick, M. (2009). Machine learning classifiers and fMRI: a tutorial overview. *Neuroimage*, *45*(1), S199-S209.

Pessoa, L. (2022). *The entangled brain: How perception, cognition, and emotion are woven together*. MIT Press.

Phelps, E. A., & LeDoux, J. E. (2005). Contributions of the amygdala to emotion processing: from animal models to human behavior. *Neuron*, *48*(2), 175-187.

Phillips, M. L., & Swartz, H. A. (2014). A critical appraisal of neuroimaging studies of bipolar disorder: toward a new conceptualization of underlying neural circuitry and a road map for future research. *American Journal of Psychiatry*, *171*(8), 829-843.

Poldrack, R. A., Huckins, G., & Varoquaux, G. (2020). Establishment of best practices for evidence for prediction: a review. *JAMA psychiatry*, *77*(5), 534-540.

Rorden, C., Bonilha, L., Fridriksson, J., Bender, B., & Karnath, H. O. (2012). Age-specific CT and MRI templates for spatial normalization. *Neuroimage*, *61*(4), 957-965.

Rossi, R., Lanfredi, M., Pievani, M., Boccardi, M., Rasser, P. E., Thompson, P. M., ... & Frisoni, G. B. (2015). Abnormalities in cortical gray matter density in borderline personality disorder. *European Psychiatry*, *30*(2), 221-227.

Saarimäki, H., Gotsopoulos, A., Jääskeläinen, I. P., Lampinen, J., Vuilleumier, P., Hari, R., ... & Nummenmaa, L. (2016). Discrete neural signatures of basic emotions. *Cerebral cortex*, *26*(6), 2563-2573.

Schmaal, L., Hibar, D. P., Sämann, P. G., Hall, G. B., Baune, B. T., Jahanshad, N., ... & Veltman, D. J. (2017). Cortical abnormalities in adults and adolescents with major depression based on brain scans from 20 cohorts worldwide in the ENIGMA Major Depressive Disorder Working Group. *Molecular psychiatry*, *22*(6), 900-909.

Schmaal, L., Veltman, D. J., van Erp, T. G., Sämann, P. G., Frodl, T., Jahanshad, N., ... & Hibar, D. P. (2016). Subcortical brain alterations in major depressive disorder: findings from the ENIGMA Major Depressive Disorder working group. *Molecular psychiatry*, *21*(6), 806-812.

Schweizer, S., Grahn, J., Hampshire, A., Mobbs, D., & Dalgleish, T. (2013). Training the emotional brain: improving affective control through emotional working memory training. *Journal of Neuroscience*, *33*(12), 5301-5311.

Shenton, M. E., Hamoda, H. M., Schneiderman, J. S., Bouix, S., Pasternak, O., Rathi, Y., ... & Zafonte, R. (2012). A review of magnetic resonance imaging and diffusion tensor imaging findings in mild traumatic brain injury. *Brain imaging and behavior*, *6*(2), 137-192.

Smith, S. M., Jenkinson, M., Woolrich, M. W., Beckmann, C. F., Behrens, T. E., Johansen-Berg, H., ... & Matthews, P. M. (2004). Advances in functional and structural MR image analysis and implementation as FSL. *Neuroimage*, *23*, S208-S219.

Thomas, K. S., Jones, C. R., Williams, M. O., & Vanderwert, R. E. (2025). Neural correlates of emotion regulation and associations with disordered eating during preadolescence. *Developmental Psychobiology*, *67*(1), e70009.

Tromp, D. P., Williams, L. E., Fox, A. S., Oler, J. A., Roseboom, P. H., Rogers, G. M., ... & Kalin, N. H. (2019). Altered uncinate fasciculus microstructure in childhood anxiety disorders in boys but not girls. *American Journal of Psychiatry*, *176*(3), 208-216.

van Dam, W. O., & Chrysikou, E. G. (2021). Effects of unilateral tDCS over left prefrontal cortex on emotion regulation in depression: evidence from concurrent functional magnetic resonance imaging. *Cognitive, Affective, & Behavioral Neuroscience*, *21*(1), 14-34.

Vo, D. T., Phan, C. C., Le, H. G. N., Vo, T. P., Mai, U. T. T., Le, H. K., & Ha, T. B. T. (2022). Diffuse axonal injury: a case report and MRI findings. *Radiology Case Reports*, *17*(1), 91-94.

Xu, E. P., Nguyen, L., Leibenluft, E., Stange, J. P., & Linke, J. O. (2023). A meta-analysis on the uncinate fasciculus in depression. *Psychological medicine*, *53*(7), 2721-2731.

Xu, E., Nguyen, L., Hu, R., Stavish, C. M., Leibenluft, E., & Linke, J. O. (2022). The uncinate fasciculus in individuals with and at risk for bipolar disorder: A meta-analysis. *Journal of affective disorders*, *297*, 208-216.

Zhou, F., Zhao, W., Qi, Z., Geng, Y., Yao, S., Kendrick, K. M., ... & Becker, B. (2021). A distributed fMRI-based signature for the subjective experience of fear. *Nature communications*, *12*(1), 6643.

Zhu, X., Wang, X., Xiao, J., Liao, J., Zhong, M., Wang, W., & Yao, S. (2012). Evidence of a dissociation pattern in resting-state default mode network connectivity in first-episode, treatment-naive major depression patients. *Biological psychiatry*, *71*(7), 611-617.