Altered orbitofrontal cortex neural variability underlies idiosyncratic experiences during aging

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Abstract

Moment-to-moment neural variability plays a crucial role in learning and behavioral flexibility. Changes in this variability have been linked to age-associated differences in both task performances and resting-state activity. However, the effect of neural variability on specific computations and subjective experience remain unclear. Here, we demonstrate that changes to cortical neural variability during naturalistic experience serves as a readout of changes to region-specific computations, distinct from resting-state variability and mean neural activity. During affective experience, older adults exhibited an increase in neural variability within the orbitofrontal cortex (OFC). By employing a Bayesian learning model, we revealed that this corresponded to heightened uncertainty in the computational estimates of evolving valence in older adults. This model prediction was observed neurally with frequent state switching and temporally distorted representations within the OFC in older adults, compared to stable representations in the young. Crucially, these representational changes mirrored the arousal responses of the two groups. These results advance our understanding of how neural variability might carry unique information in aging, particularly to their changing and possibly idiosyncratic affective experiences.

Introduction

Neural responses are inherently variable[1,2]. What was once considered as "noise" is now increasingly being recognised as a crucial part of efficient neural processing[2–4]. A growing body of research has shown that cortical signal variability plays a key role in higher-order cognition[5,6], allowing for flexible navigation of task-specific demands[5,7,8]. This is strongly supported by theoretical frameworks suggesting that neural variability reflects a statistically optimal representation of task uncertainty[9,10]. This interpretation of neural variability as a cognitive facilitator is leveraged in aging neuroscience to compare how cognitive demands affect this measure across lifespan[11–13]. However, studies often show highly region-specific[14] and task-specific results[6,15], making a generalised directional claim between neural variability and experience tenuous. This highlights the need to contextualise neural variability within specific regions and under relevant theoretical models. Conversely, studies on intrinsic, resting-state signal variability make it difficult to link to experience and specific theoretical frameworks outlined above due to the absence of an explicit task[4]. Combining naturalistic neuroimaging with theoretical modelling offers a promising approach to explore how variability-based regional differentiation relates to experience. In this study we explore how aging alters this relationship.

A richly dynamic and socially complex movie requires one to flexibly navigate an array of internal and external affective states. Orbitofrontal subregions in the prefrontal cortex have been implicated in a multitude of affect-related studies[16,17] and have strong theoretical underpinnings to learning[18]. Specifically, its medial and lateral sectors are thought to play complementary roles in affective computations[16]. The medial orbitofrontal cortex (mOFC) or ventromedial PFC is a core region involved in learning schemas[19], state estimation[20] and fluctuates between affective states[21]. In contrast, the lateral orbitofrontal cortex (lOFC) is mostly externally focused, predicts state transitions[22], stimulus-outcome associations[23] and is involved in predictive tracking of affect[16]. In short, both these regions show strong ties to affective experience in naturalistic experiences. Moreover, theoretical frameworks suggest that these regions are involved in estimating state uncertainty and its dysfunction can have implications in affective disorders[24]. Changes to BOLD signal variability in these regions with age, should then exhibit broader changes to affective experience (Figure. 1a). For example, the mean neural activity might be similar in both young and older adults for a brain region. However, the neural variability of the same region can show

differential patterns between the two groups. Such variability-based regional change would likely be specific to the 'task-evoked' variability rather than intrinsic, resting-state variability[4,6]. Linking this to theoretical models of optimal task variable representations would offer testable model predictions to compare with neural data.

In the present study, we explore this variability-based regional differentiation in the context of aging. We particularly investigate how the task-evoked neural variability relates to the age-associated changes in affective experience. Employing Bayesian modelling on large-scale neuroimaging and behavioral data, we show that older adults show significantly higher BOLD variability in the lateral and medial OFC, during naturalistic experience. Notably, the differences in their prefrontal variability were specific to the stimulus-evoked neural variability and not their resting-state neural variability. Crucially, the mean neural activity of the lOFC and mOFC showed no difference between the two groups. A Bayesian learning model revealed that the increased neural variability in lOFC and mOFC in older adults was linked to a suboptimal computation of the evolving valence estimations. Furthermore, older adults showed a scattered latent state representation within their lOFC and mOFC compared to a highly coherent pattern in the young. This resembled the moment-by-moment subjective emotional experience in both groups. Taken together, these results highlight the biological importance of regional BOLD signal variability and its effect on the affective experience during healthy aging.

Results

Neural variability during naturalistic experience is distinct from resting-state variability

Our aim was to investigate how the neural variability alters with aging in response to a naturalistic affective task (Figure. 1a). For this, we first modelled the BOLD by regressing out the averaged CSF and White Matter timeseries, along with the 6 motion parameters. The residuals were used for further analyses[25]. We quantified the neural variability as the standard deviation of the normalized, filtered and demeaned BOLD time series (SD_{BOLD}) for both young and older adults for the movie (~8mins) and the resting state (~9mins) conditions. This enabled us to assess whether changes in neural variability reflect intrinsic traits or are induced by the affective states elicited by the movie.

We focused our analyses primarily on the prefrontal regions given their role in higher-order cognition and affective processing as well as evidence from our previous study[16]. The regions of interest included the prefrontal regions – anterior cingulate cortex (ACC), dorsomedial cortex (dmPFC), dorsolateral prefrontal cortex (dlPFC), medial prefrontal cortex (mPFC), ventrolateral prefrontal cortex (vlPFC), lOFC and mOFC, visual cortex (VC), Precuneus (Prec) and posterior cingulate cortex (PCC), the latter two being core Default Mode Network regions. To determine whether the engagement in older adults varies as a function of the emotional content of the stimulus, we also performed an engagement analysis (shown in Figure S6). Next, we constructed a Bayesian hierarchical regression with the SD_{BOLD} from the movie and the rest as the dependent variables. The model also included random effects of participants, including random slopes for the fixed effects to capture participant-level variance across the movie and rest. This allowed us to assess whether the BOLD variability associated with these regions is driven primarily by structural changes with age. Posterior evidence for each hypothesis was quantified through Bayes factors. However, we observed a significant increase in the SD_{BOLD} for the older individuals for the movie and not the rest (Movie: $P = 1$, BF = 415; Rest: $P = 0.96$, BF = 21) (Figure. 1b, c).

Neural variability offers unique information not captured by mean neural activity

One possibility is that the BOLD signal varies as a function of age affecting both the mean activity and variability of the young and older adults during the movie-watching task. This led us to investigate if the neural variability reflects a distinct source of information in contrast to the mean neural activity between the two groups. We computed the averaged BOLD signal for the movie-watching task and applied a Bayesian hierarchical regression using the previous model structure. No significant difference was found between the mean BOLD activities of the two groups (Figure. 1d) (Movie: $P = 0.83$, BF = 4.89).

The above results suggest two key points. First, the increase in cortical BOLD signal variability observed in healthy aging represents a task-specific effect unobserved in the resting state. Second, within naturalistic settings, neural variability provides distinct insights than those captured by the mean neural activity.

Increased movie-evoked neural variability within lOFC and mOFC in older adults

Our findings so far suggest a distinct change in the task-specific neural variability between the two groups. Next, we wanted to focus on how these changes manifest at the regional levels and affect their corresponding functions in naturalistic experience. We particularly focused on the two subregions of the OFC known to mediate affective computations in naturalistic experiences. This is also evidenced from our previous study which identified a distinct role of the lOFC and the mOFC in mediating affective experience during movie watching[16]. We compared the SD_{BOLD} of the lOFC and mOFC between the young and older adults during the movie-watching task. We observed similar pattern in the neural variability of these two regions with age (Figure. 2a, b). Older adults exhibited significantly higher SD_{BOLD} in the lOFC (Figure. 2a) (Young: β_{mean} = -0.08, 95% HDI = [-0.12, -0.04], P = 0.99; Old: β_{mean} = -0.03, 95% HDI = [-0.07, 0.007], P = 0.94), as well as the mOFC (Figure. 2b) (Young: β_{mean} = -0.06, 95% HDI = [-0.10, -0.02], P = 0.99; Old: β_{mean} = 0.08, 95% HDI = [0.04, 0.12], P = 0.99). Since our study particularly focuses on OFC which is particularly susceptible to head motion-related artifacts, we also investigated this through a more stringent preprocessing pipeline by applying ICA-AROMA prior to calculating BOLD variability. This was done to ensure that the observed differences were not majorly driven by the motion related artifacts in older individuals (Figure S2a, b). We observed a similar pattern of increased neural variability for both the OFC subregions.

To determine whether these task-evoked changes in neural variability in older adults represented a general aging effect, we compared their mean neural activity for the movie-watching task. No significant differences were found between the groups in the BOLD means for either the lOFC (Young: β_{mean} = 0.003, 95% HDI = [-0.009, 0.02], P = 0.70; Old: β_{mean} = 0.002, 95% HDI = [-0.008, 0.01], P = 0.67) or mOFC (Young: β_{mean} = -0.004, 95% HDI = [-0.01, 0.009], P = 0.74; Old: β_{mean} = -0.005, 95% HDI = [-0.02, 0.006], P = 0.81) (Figure S3).

Additionally, we also compared the SD_{BOLD} of dlPFC and mPFC between young and older adults, to assess the age-related changes in the neural variability. These prefrontal regions are often involved in attentional control and social processing respectively, both of which can change with age. No significant differences were observed in the neural variability between the two groups for these regions (Figure. 2 c,d) (dlPFC: Young: β_{mean} = 0.02, 95% HDI = [-0.02, 0.06], P = 0.89; Old: β_{mean} = 0.001, 95% HDI = [-0.03, 0.03], P = 0.53; mPFC: Young: β_{mean} = -0.006, 95% HDI = [-0.05, 0.03], P = 0.61; Old: β_{mean} = -0.02, 95% HDI = [-0.05, 0.02], P = 0.82). We also observed a

similar pattern of neural variability between the groups for these regions using the ICA-AROMA pipeline (Figure S2c, d).

These above results indicate that regional BOLD variability provides distinct neural signatures of aging that are not captured by mean BOLD activity alone. Additionally, the increased neural variability trends observed in the OFC may indicate an age-related shift in processing during naturalistic settings within this region.

Changes in neural variability underlie suboptimal computations of valence in the OFC in older adults

Increased neural variability has been suggested to facilitate dynamic behavioral switching based on task-specific demands. Similarly, theoretical frameworks propose that neural variability efficiently encodes stimulus-specific uncertainty during tasks[10]. Our previous study elaborated on the role of orbitofrontal regions in encoding uncertainty during affective processing[16]. We have shown that these regions are involved in optimally encoding the uncertainty around the evolving valence in the movie. Thus, an altered BOLD variability in these regions may reflect an altered valence processing during affective experience.

To investigate how the young and older adults compute this uncertainty around valence, we implemented a Bayesian learning model termed as Hierarchical Gaussian Filter model (HGF) (Figure. 3a). First, we collected the continuous valence ratings from two independent groups of young and older adults for the movie (Figure. 3b). Next, we deployed multiple 3-level HGF models to fit the averaged valence ratings of each group separately. This model has been extensively used in learning, decision-making, and affective dynamics[26–28]. In this model, the averaged valence time-course of each group is used as the input. With this input, the first layer, x_1, models the probability of the valence at each time point. The next level, x_2, estimates the underlying uncertainty associated with the predictions on the valence. Finally, the third level x_3 estimates the overall volatility or the meta volatility associated with the valence. This indicates the rate at which the belief on the uncertainty around valence changes. This can also be described as one's belief in how stable the movie contexts are, given the valence dynamics. The belief updates are primarily governed by 2 parameters - $\boldsymbol{\omega}$ and $\boldsymbol{\vartheta}$, which influence the estimated uncertainty (second-level) and volatility (third-level) trajectories about the valence respectively. Here, we wanted to dynamically

model the averaged valence rating of the elderly by lesioning these two free parameters - $\boldsymbol{\omega}$ and $\boldsymbol{\vartheta}$.

We initially used the HGF model fitted to the young group (from our previous study)[16] as the 'baseline' model. Following this, we simulated multiple models, each with a specific lesioning in $\boldsymbol{\omega}$ and $\boldsymbol{\vartheta}$ parameters. We then fit these models to the older cohort's group-averaged valence time-course. We hypothesized that the model best-fitting the older adults' task-specific variable (valence) would deviate from the 'baseline' parameters. This deviation would then reflect specific changes in the estimation of uncertainty around the valence, reflective of their observed differences in the neural variability of the OFC. A reduced $\boldsymbol{\omega}$ in the older adults would suggest a decreased prediction uncertainty around the valence dynamics, thus slower updation to the changing valence. In contrast, an increased $\boldsymbol{\omega}$ will signify increased uncertainty around the predictions of valence, thus faster updation to the changing valence. The meta-volatility parameter $\boldsymbol{\vartheta}$, on the final level, determines the belief about the model's beliefs in the movie volatility. Lower values denote higher beliefs in the stability of the movie context, and vice versa.

Model inversion was conducted by variational inference, and model adjudication was done by selecting the one with the highest log-model evidence (LME) (Figure. 3c) (Table 2). The best-fitting model showed an increased $\boldsymbol{\omega}$ (Figure. 4a) suggesting an increased variance (uncertainty) around the valence in the elderly. Concurrently it also showed a decreased $\boldsymbol{\vartheta}$, denoting an increased belief in the stability of the context of the movie. Figure 2a, b shows that older adults exhibited increased variability in the lOFC and mOFC than younger adults, mirroring the model parameters in level 2. This suggests that an increased variability occurs in both the neural level (BOLD) and model output (valence) from the same stimuli as a function of aging.

A more direct prediction of the model is that older adults would show more frequent prediction updates due to their increased $\boldsymbol{\omega}$ (Figure. 4a). Based on our previous findings that the OFC tracks uncertainty around valence during naturalistic movie viewing[16], we hypothesized that older adults would show more frequent neural transitions in these regions compared to younger adults. We used Hidden Markov Models (HMMs) to obtain these neural transitions (see Methods for details). We found that both lOFC and mOFC showed more stable transitions in the young adults (Figure. 4b left). However, both these regions both showed more frequent latent state transitions in older

adults (Figure 4b right). Interestingly, the belief update trajectories in the older adults also showed more frequent updates compared to that of the young.

We also compared the HMM state transitions of the visual cortex as a control ROI for the two groups (Figure 4c and S7). This was to rule out the effect of sensory or perceptual uncertainty processing. Both groups exhibited similar transitions with no distinct pattern, suggesting that the observed differences in orbitofrontal regions are due to top-down processes rather than perceptual differences.

In summary, an increased neural variability in older adults within OFC reflected a suboptimal computation of the uncertainty around the valence. This also corresponded with faster latent state transitions within the older adults in contrast to more stable transitions within the OFC of the younger adults, aligning with Bayes-optimal prediction updates.

Disrupted OFC dynamics links to variable emotional experience in aging

Our findings so far suggest that older individuals exhibit a suboptimal computation of uncertainty around the valence, which may be linked to the altered neural variability in the lOFC and mOFC. While the computational model hinted at this relationship, we have not yet directly examined how these regions relate to affective experience. To explore this, we collected continuous ratings of Arousal for this movie from two independent groups of young and older adults. Arousal reflects the global emotional intensity of the movie, capturing elements beyond valence, such as attention-driven mechanisms. Unlike valence, the two groups showed significant difference between their arousal ratings, with older adults displaying lower and more variable arousal (Figure. 5, inset) ($r = 0.67$, $p < 0.001$). This effect was most pronounced during emotionally intense scenes, as rated by the young group.

The lOFC and mOFC exhibited patterns of increased neural variability and qualitatively reflected distinct profiles of prediction updates of the two groups. This led us to hypothesise that these regions may show different latent representational patterns underlying the affective experience during the movie in the two groups. To this end, we leveraged a non-linear dimensionality reduction method, Temporal-PHATE on the BOLD timeseries of these regions (see Methods for full description). This method has been shown to capture the sequential progression of neural activity onto a low-dimensional space, revealing how these regions transition across time. This

would recover the sequential trajectory of 'latent states' these regions would navigate during naturalistic experience on a group level.

In the young adults, the latent representation in the lOFC (Figure 5a) and mOFC (Figure 5b) followed a preserved temporal sequence during movie-watching. Older adults, by contrast, revealed a more temporally disrupted sequence (Figure 5a, b). Crucially, the arousal responses showed the greatest differences between the groups at the time points where the latent sequences in the orbitofrontal cortex (OFC) were most disrupted in the older adults. Despite originating from two distinct groups, this consistency between neural data and behavioral ratings underscores the reliability of these results. The latent representation in mOFC also displayed different temporal trajectories between the two age groups (Figure S5).

Overall, these results provide novel insights into the nature of regional neural variability linked to healthy aging, optimal computations, and, most importantly, our affective experience.

Generalizing age-related emotional variability to multiple tasks

Next, we considered whether the emotional variability observed in the movie task could be generalized to other emotional tasks with different formats. It is important to rule out the possibility that the neural variability observed was specific to movie demands (plot complexity, working memory load, etc.). We analyzed data from the scanning cohort on two separate behavioral tasks.

First, we examined a task where participants reported the displayed emotion on a morphed facial expression image (FER). Participants chose from six emotion categories: Happy, Sad, Anger, Fear, Disgust, and Surprise. We compared the individual variability of each participant by computing the standard deviation (SD) of their accuracy over all six categories. Older adults had a significantly higher SD than young (mean-SD_Y = 11.08, mean-SD_O = 17.44, t = -5.17, $p < 0.0001$, Cohen's d = 0.73) (Figure. 6a). Interestingly, between-group variability for each of the 6 emotions showed a similar pattern of increased idiosyncrasy in older adults (Happy: SD_Y = 2.68, SD_O = 5.99; Sad: SD_Y = 5.02, SD_O = 19.31; Anger: SD_Y = 19.52, SD_O = 27.4; Fear: SD_Y = 15.4, SD_O = 23.54; Disgust: SD_Y = 20.28, SD_O = 20.63; Surprise: SD_Y = 8.04, SD_O = 13.32) (Figure. 6b). Thus the emotional variability was not only present but it showed aging related effects in each of the separate emotions.

Next, we analyzed data from a task where participants watched short video clips (~30s) of Neutral, Negative, and Positive valence and provided a single rating (0-100) of their emotional experience. Here we could not obtain the individual variability due to the nature of the task but instead obtained the between-group SD of their ratings for each condition. All 6 conditions (see Methods for details) showed a consistent increase in variability in old irrespective of the valence (NegW_pos: SD_Y = 0.47, SD_O = 1.75, NegW_neg: SD_Y = 1.38, SD_O = 2.43; PosW_pos: SD_Y = 1.90, SD_O = 2.36; PosW_neg: SD_Y = 0.74, SDO = 1.47; NeuW_pos: SD_Y = 1.18, SDO = 2.29; NeuW_neg: SD_Y = 0.40, SD_O = 1.42) (Figure. 6c).

Discussion

The key advance of our work is to show how regional BOLD variability indicates a physiologically unique signature in aging. Importantly, the changes to cortical neural variability in older adults show distinct patterns in naturalistic experience compared to mean neural activity as well as resting-state variability. This is in line with theoretical frameworks that posit task-variable computations require navigating different regimes flexibly, which may be compromised in aging[12]. We found valence-related processing in orbital prefrontal regions shows specific age-related changes in their neural variability in its medial (mOFC) and lateral (lOFC) subregions. Moreover, a Bayesian learning model suggested older adults had increased uncertainty around valence computations. Additionally, the model showed concordance with neural transitions within OFC in young, but much less in old, suggesting deviation from optimal computations. Changes to the latent representations in the regions closely resembled the affective experiences of both young and older adults. These results advance our understanding of how neural variability might carry unique information in aging, particularly with regards to their idiosyncratic affective experiences.

Neural variability is usually studied on cognitively demanding tasks (e.g. working memory) or resting-state variability[6,7,11,12,14]. These studies provide a wealth of results in terms of its various neurobiological properties and alterations in healthy aging[29]. While some studies link increased neural variability to deteriorating performance in tasks like working memory[8], others demonstrate the opposite trend. The pattern of change also varies across different brain regions. Unlike specific task-based studies, naturalistic paradigms require coordinated dynamics across multiple forms of higher-order cognition, making them more ecologically similar to real-life experiences[30,31]. Leveraging Bayesian hierarchical modelling allowed us to incorporate multiple, related sources of information within the data. Specifically, this ensured that we captured both individual, group-level and condition-specific effects on neural variability. In doing so, we found a significant increase in neural variability in older adults compared to young. Critically the evidence for this increase was much smaller in intrinsic, resting-state BOLD variability. This comparison provides strong evidence that neural variability modulated by naturalistic experiences differs from spontaneous, resting-state activity. In contrast, the mean neural responses (BOLD mean) showed no differences among the young and old. This strongly suggests that the mean and SD of the physiological BOLD signal carry fundamentally different sources of information in aging[29].

A variety of information is processed during naturalistic stimulation. We focused on an important variable related to emotion processing - continuous valence information. In addition, we focused on the OFC because of its critical role in affective processing[16]. Studies have shown that its lateral subregions (lOFC) underpin distinct functional roles than its medial counterparts (mOFC)[32,33]. Here, we observed a distinct trend within the OFC for these two regions. Both lOFC and mOFC exhibited higher neural variability in older than younger adults. Importantly, these differences in variability could not be attributed to the differences in perceptual processing in the visual cortex. Moreover, the mean neural activity showed no differences among the groups, in both these regions. These results suggest that variability in BOLD signals during movie viewing may reflect age-related alterations in affective processing.

Theoretical models posit that neural variability represents optimal task computations and uncertainty representations[4,9,10]. Optimally representing task-uncertainty comes under the purview of Bayesian frameworks of cognition[34]. To explore the effect of increased neural variability at the computational level during naturalistic affective experience, we used a hierarchical Bayesian learner [28] which was given the valence responses in the movie. In our previous study, a normative variant of this model showed how uncertainty computations arise from valence in the same younger individuals[16]. Using this as our baseline, we adjusted two key parameters underlying uncertainty computations in different ways. This was to test several competing accounts of suboptimal computations happening in aging[26,35,36]. This allowed us to use the same model architecture to assess deviations in older adults compared to young. The winning variant showed considerably higher variance around predicting valence for the older adults. That is, older adults had a heightened uncertainty around predicting how the valence changes in the movie. To link the neural findings with the model output, we compared prediction updates in the model to that of the latent state transitions in the OFC. Neural state changes during naturalistic stimuli are closely linked to the movie experience, although several factors might underlie these changes within a region. Here, we found qualitative similarities between OFC transitions and prediction updates to valence in the young. In contrast, the older adults showed more variable neural transitions. This suggests that neural transitions here may reflect suboptimal estimation of valence uncertainty in these regions. Overall, increased uncertainty around the valence coupled with increased neural variability in lOFC suggests that older adults may experience less stable or more variable emotional experiences.

Neural variability indexes how adaptive a region is to task variable changes and demands. Although a one-to-one correlation might be misleading, changes to this measure are expected to have an impact on the general cognition the specific task variable governs. In our study, we hypothesised that a suboptimal computation of emotional valence might affect the overall affective experience. Using T-PHATE, we projected neural representations of the OFC regions onto a low-dimensional space, uncovering latent state trajectories across the two groups. The stark differences observed in the lOFC were highly similar to their respective arousal time-courses. Specifically, a sequentially preserved representation observed in the young group mirrored their stable arousal dynamics. In contrast, the distorted patterns observed in older adults' lOFC paralleled their lower and more variable arousal. Cognitively demanding tasks such as working memory require representing and navigating a higher dynamic range of states to perform optimally. Affective tasks, in contrast, are more inferential in nature[37]. As a result, there is an inherent uncertainty in one's interpretations of emotional experiences. Here, representing a wider gamut might actually be misleading (at best) or paralyzing (at worst). Indeed, misestimation of uncertainty, a known factor in psychiatric disorders [24,38], may similarly underlie the idiosyncratic affective experiences in aging. In affective tasks, the lOFC helps predict how emotional states will change over time, integrating information about uncertainty to guide decision-making[18,22]. The higher variability observed here in the older cohorts seems to be consistent with our model results and reward learning studies. Taken together, this suggests that a failure to compute the uncertainty around the valence by the OFC might underlie the consistently idiosyncratic affective experiences seen in aging.

There are inherent limitations to interpreting BOLD signal variability in any task. For example vascular and non-cognitive process may play a significant role[29]. We took steps to mitigate these influences, by regressing motion as well as the CSF and white matter signals. Another potential critique is the use of two separate behavioral and neuroimaging groups in this study. However, the alignment between model prediction updates and neural transitions supports the validity of this approach. Moreover, we generalized the results of variability in emotions in the scanning cohort to two separate tasks requiring processing of valence. Our confirmation of similar patterns of shared neural responses in the movie for the two groups also rules out attentional processing-related accounts.

Overall, we contribute a strong case for the physiological BOLD signal variability as a readout of regional computations, separate from resting-state and neural mean activity. The changes to this signal in healthy aging, captured in a naturalistic setting offered a window to their idiosyncratic experience. More nuanced questions on various forms of uncertainty can affect the variability remain – but we hope to have furnished a potential framework for answering them.

Methods

Participants

We divided our participant pool into two groups – Young (18-35 years) and Old (60-88 years). After preprocessing, a total of 209 individuals (Young: N = 111, µage = 28.5±4.9, Male = 48; Old: N = 98, µage = 77±5, Male = 45) were selected from the healthy population derived Cambridge Centre for Aging and Neuroscience (CamCan) cohort for this study[39,40]. We extracted the behavioral responses of these participants for the Facial Emotion Recognition (FER) and Emotional Reactivity and Regulation (EmoR) tasks. Owing to missing data, the final sample size for the FER was 203 (Y = 108, O = 95) and that of EmoR was 91 (Y = 49, µage = 28±5; O = 42, µage = 76.9±5.7). All participants provided their informed consent, and the data was collected in accordance with the Cambridgeshire Research Ethics Committee.

Additionally, we recruited independent groups of participants on an online platform (Prolific) to collect continuous ratings for arousal, valence and uncertainty for the same movie shown to the neuroimaging participants. 40 participants were recruited for each group (N=80), age and demographically matched with the fMRI individuals (UK). All participants were screened based on educational qualification and mental health status to reduce potential confounds and reported no previous history of watching this movie. The study was approved by the Institutional Human Ethics Committee of the National Brain Research Centre, India (NBRC).

Stimulus

Our main behavioral and neuroimaging analyses were centred on a short, suspenseful movie called "Bang! You're dead" (~8mins) by Alfred Hitchcock.

Continuous behavioral rating task

Four independent groups of participants continuously rated the movie for valence and arousal using a vertical slider on Prolific (Table 1). After rejecting subjects with missing data, this resulted in a final sample of 97 participants (Y: N = 34, µage = 24.5, Male =16; O: N = 30, µage = 67.8, Male = 14). For each group, we z-scored the participants' responses and smoothed the averaged time courses using local regression smoothing (loess).

392 **fMRI acquisition and preprocessing**

393 The fMRI data for the movie-watching and the resting state sessions were provided by the
394 CamCan[39]. The functional scans for the movie-watching session were acquired using a T2∗-
395 weighted echo planar imaging pulse sequence (TR = 2470 ms; TE = 9.4 ms, 21.2 ms,33 ms, 45
396 ms, 57 ms; 32 axial slices; slice thickness = 3.7 mm; FOV = 192 × 192 mm; voxel size = 3 × 3 ×
397 4.44 mm), leading to a total of 193 volumes. The functional data for resting state was acquired
398 using the same pulse sequence and acquisition parameters with a TR of 1970 ms. The acquisition
399 time for this session was 8 min 40 s, which resulted in 261 functional volumes. The first 4
400 functional volumes of both sessions were discarded from the main analyses.

401 Neuroimaging data from both sessions were preprocessed in MATLAB (2019b) using Statistical
402 Parametric Mapping (SPM12) (https://www.fil.ion.ucl.ac.uk/spm). The preprocessing steps
403 included spatial realignment, slice-timing correction, coregistration of functional (T2) to
404 anatomical (T1) scans, affine transformation to Montreal Neurological Institute template
405 (MNI152), resampling to 2 mm isotropic voxels, and spatial smoothing with a 6 × 6 × 9-mm full-
406 width at half-maximum Gaussian kernel. Whole-movie GLM was computed by regressing six
407 motion parameters (X-, Y-, Z-displacement and pitch, roll, and yaw parameters) by least square
408 regression. We excluded subjects with maximum framewise displacement >2.5 mm or 1.5° from
409 further analysis. The extracted BOLD data were detrended and band-pass filtered (0.01–0.1 Hz)
410 using a second-order Butterworth filter.

411 **Region-of-interest (ROI) definition**

412 We focused our analyses on the prefrontal cortical regions due to their critical role in mediating
413 higher-order cognitive functions, such as affect[16,41,42], and their involvement in naturalistic
414 tasks[43,44].

415 For the neural variability analyses of the movie and resting state, we included 8 prefrontal ROIs –
416 anterior cingulate cortex (ACC), dorsolateral PFC (dlPFC), dorsomedial (dmPFC), ventrolateral
417 PFC (vlPFC), medial PFC (mPFC), medial orbitofrontal cortex (mOFC) and lateral orbitofrontal
418 cortex (lOFC), posterior cingulate cortex (PCC). We also incorporated the visual cortex (VC) and

Precuneus because of their roles in sensory and multi-sensory processing. All ROI masks were adapted from our previous work, where additional details can be found [16].

Bayesian Hierarchical Regression (BHR) to model the effect of movie and resting state on neural variability and mean neural activity

First, we computed the neural variability as the standard deviation of the BOLD signal (SD_{BOLD}) for the movie and the resting state. BOLD signals were extracted for each session from the residuals after regressing out signals from white matter, cerebrospinal fluid (CSF), and motion-related artifacts. Thereafter, the BOLD timeseries was normalised, filtered and centered for each ROI for both groups. We also followed an alternate pipeline to extract the BOLD which included applying ICA-AROMA before regressing out the CSF, WM and Motion artifacts. Our region-specific result followed the same pattern, albeit with reduced differences (Figure S2). Furthermore, we also compared the raw SD_{BOLD} values for both the pipelines. We found similar patterns of increased variability for both the lOFC and mOFC, as well as an insignificant difference in VC (Figure S4). ICA-AROMA might be more conservative in removing movie-related signals, and thus, to preserve those for our further analysis, we instead followed our former pipeline, which follows as described in[25].

Next, we modelled the effect of rest and movie with age on the BOLD variability of the participants, using a BHR. The dependent variable for the model input was given by the SD_{BOLD} of 9 ROIs which included all prefrontal ROIs (mOFC, mPFC, dmPFC, lOFC, vlPFC, dlPFC, ACC, PCC) along with VC and Precuneus.

The SD_{BOLD} of each session (Rest/Movie) for each subject was modeled as a Student *t*-distribution:

SD_{BOLD} = Student $t\ (\nu, \mu, \sigma)$,

where ν is the degrees of freedom, σ is the scale parameter of the distribution, and μ is the mean which can be expressed as:

$$\mu = \beta_0 + \beta_1 . \text{Group} + \gamma_{0\text{Subj}} + \gamma_{0\text{ROI}}$$

$$+ \gamma_{1i} . \text{Group} \mid \text{ROI}$$

$+ \gamma_{2j}$. Group | Subject

$+ \varepsilon_{ij}$.

Here, β_0 is the overall intercept, γ_{0ROI} is the varying intercept over i ROIs, γ_{0Subj} is the varying intercept over j participants. β_1 reflect the slope of the predictor, which is the group, (Movie and Rest with Age ; four groups). γ_{1j} indicates the varying slope term for the group across each ROI. Likewise, γ_{2j} , indicates the group slope varying across all i (=209) participants. ε connote the population-level variance terms. Weak, noninformative priors were applied over the model terms. This model incorporated the effect of rest and movie, while simultaneously accounting for within-group and between-group variability on the level of ROIs. For more details, see supplementary section 1 (Figure S1).

$\beta_0 \sim$ Student t (3, 0.5, 2.5)

$\beta \sim$ Student t (3, 0, 2.5)

$\gamma_0 \sim$ Student t(3, 0.5, 2.5)

$\gamma \sim$ Student t (3, 0, 2.5)

$\varepsilon \sim$ Half Student t (3, 0, 2.5)

An evidence of $P > 95\%$ is equivalent to the frequentist depiction of significant P-values. In addition, we also quantified the effect size by computing the BF (calculated by the Savage-Dickey ratio).

A similar model was used to examine the effect of movie and resting-state conditions on mean neural activity across age groups, using the same ROIs. In this model, the standard deviation of BOLD (SD_{BOLD}) was replaced with the average BOLD activity for each ROI.

Behavioral modelling - Hierarchical Gaussian Filter (HGF)

To investigate how the age-associated changes in task-evoked neural variability affect the computation during affective experience, we compared and contrasted multiple variants of the 3-level hierarchical Gaussian Filter (HGF)[28]. The HGF is a Bayesian learning model [28], which can

be used to fit and recover parameters from a participant's behavioral data or simulate models with different parameter configurations, scored on Log Model Evidence (LME). In brief, by employing variational Bayes, this model can infer an individual's belief and uncertainty trajectory of hidden environmental states, which are modelled as a hierarchy of coupled Gaussian random walks. Since we did not have any behavioral response from the neuroimaging participants, we only used a perceptual model on a Bayes-optimal agent with the average valence ratings of each group as the input using the TAPAS toolbox (http://www. translationalneuromodeling.org/tapas/). With this input, the first layer, x_1, models the probability of the valence at each time point. The next level, x_2, estimates the underlying uncertainty associated with the predictions on the valence. Finally, the third level x_3 estimates the overall volatility associated with the valence, i.e., the rate at which the belief on the uncertainty around valence changes. In this study, this level can signify the belief in the environmental stability or the context of the movie. These levels are related to each other with regard to the step-size of a Gaussian random walk. A prediction error, i.e., a misestimation of the valence at the lower level, will cause an update at the higher levels. These levels are coupled to each other by parameter $\boldsymbol{\kappa}$, which denotes a phasic, temporally varying parameter that determines the scaling of the volatility. Since we did not have any specific hypotheses on how this coupling might change with age, we kept $\boldsymbol{\kappa}$ the same for both groups. Our main hypotheses rested with the $\boldsymbol{\omega}$ and $\boldsymbol{\vartheta}$ parameters that denote a tonic, time-invariant parameter for the second and third levels, respectively. $\boldsymbol{\Omega}$ captures the degree to which an agent updates his belief about the rate of valence change $x_2^{(k)}$ independent of the volatility, and $\boldsymbol{\vartheta}$ determines meta-volatility or the variance of the agent's volatility.

The HGF is commonly implemented to dynamically model learning under uncertainty. However, previously, this model had enabled us to uncover a predictive architecture where the volatility trajectory estimated from the valence ratings reflected the subjective uncertainty of the participants[16] during affective experiences. In this study, our goal was to test a few competing hypotheses, especially whether the older adults differed regarding 1) the computation of the variance around the fluctuating valence across the movie and 2) updating their belief trajectory in the face of changing uncertainty on the valence. Thus, this can be construed as a form of model

'lesioning' wherein a normative model that explains a behavioural quantity and its latent parameters are altered, such that qualitative predictions similar to the data can be assessed.

To formalize these predictions, we simulated multiple models manipulating 2 free parameters $\boldsymbol{\omega}$ and $\boldsymbol{\vartheta}$ (Table 2), the tonic parameters for the second and third level respectively. An increase in $\boldsymbol{\omega}$ would indicate a higher uncertainty estimate (at the 2nd level) on the changing valence, whereas its decrease would indicate vice-versa. The meta-volatility parameter $\boldsymbol{\vartheta}$, influences the belief updates on the volatility (3rd level) of the valence. The resultant belief trajectories were visually inspected and after considering the Log-Model Evidence (LME), we selected the best model which could offer a parsimonious explanation of the age-associated changes during naturalistic experience in older adults.

To analyse the effect of $\boldsymbol{\omega}$ on the variance of belief around the changing valence we compared the belief update trajectories (ud2) of both groups.

Hidden Markov Model (HMM)

Next, we wanted to explore how the age-associated computational changes is reflected in the latent state representations of the orbitofrontal cortex during naturalistic experience. For this, we fit an HMM to the individual subject's BOLD time series of lOFC, mOFC and VC (for control) for both groups, generating a single emission sequence across all participants of a group. Multiple models were created from pre-specified states of range 2 to 10 which were then adjudicated by selecting the one with the least Bayesian information criteria (BIC). Parameter estimation for the models was done using the Baum-Welch algorithm (a variant of the Expectation-Maximization algorithm) by iteratively maximizing the expected joint log-likelihood of the parameters, given the observations and states. Decoding was done by the Viterbi algorithm by computing the maximum a posteriori state sequence for each of the HMMs. Thereafter, we compared the update trajectories from the HGF with the HMM state transitions of the orbitofrontal cortex subregions for the two groups.

Temporal Potential of Heat-diffusion for Affinity-based Transition Embedding (PHATE)

Finally, we sought to explore, how these representational changes in the OFC affect the subjective experience in the two groups. We implemented a non-linear, unsupervised dimensional-reduction

technique called temporal PHATE (T-PHATE) [45]. PHATE is recognized for its distinct advantages compared to conventional dimensional-reduction techniques like PCA and tSNE, as it effectively preserves both local and global data structures. Additionally, its non-linear nature and ability to capture the temporal evolution of a component present in the stimulus makes it well-suited for naturalistic paradigm.

It considers an input matrix of TR x Voxel, on which it computes the Euclidean distance D between two TRs, where, $D(i, j) = ||X_i, - X_j,||^2$. Then it converts this matrix into a local affinity matrix K using an adaptive bandwidth Gaussian kernel. The affinity matrix K is then row-normalized to get the initial probabilities P, which are used for the Markovian random-walk diffusion process. The diffusion operator P is then raised to the t_D^{th} power, where t_D is the PHATE optimal diffusion time scale, to perform a t_D-step random walk over the data. This specific diffusion process effectively infers more global relations beyond the local affinities. To further preserve both the local and manifold-intrinsic global structure of data, PHATE computes the diffusion potential distance P_D between the distribution at the ith row $P^{tD}{}_i$ and the distribution at the jth row $P^{tD}{}_j$.

$$P_D(i,j) = \sqrt{\sum_k \left(\log\left(P^{t_D}(i,k) - P^{t_D}(j,k)\right)\right)^2}$$

The potential distance is finally embedded with a distance embedding method (multidimensional scaling - MDS) for final visualisation. This embedding accurately visualizes trajectories and data distances, without requiring strict assumptions typically used by path-finding and tree-fitting algorithms. T-PHATE is a modified PHATE algorithm which is able to capture the temporal aspect of the data. The algorithm works the same as the original PHATE except for the temporal component infused in the diffusion matrix using the auto-covariance function in a Temporal Affinity Matrix[45].

Behavioral tasks on Emotion processing

Facial Emotion Recognition task

Participants were presented with a series of emotional faces and for each trial, they had to characterize the emotion from six emotion categories – happy, sad, anger, fear, disgust, and

surprise. Ee investigated the within-group and between-group behavioral variability (SD) across all categories and for each category respectively for both groups.

Emotional Reactivity and Regulation task

Participants viewed short video clips of 30 seconds, chosen from a wide range of videos categorized into Positive (e.g. Babies playing), Negative (e.g. Accident) or Neutral (e.g. Workplace demonstration) clips. The presentation of the video was preceded by a cue to watch or regulate. For our study, we only selected the responses to the Watch condition, where participants were instructed to rate their emotional response on scales of 0 – 100 on how positive and negative they felt after each clip. Thereby, for each group, their behavioral ratings were classified into 6 types – Negative-watch-Negative (NegW_neg), Negative-watch-Positive (NegW_pos), Positive-watch-Negative (PosW_neg), Positive-watch-Positive (PosW_pos), Neutral-watch-Negative (NeuW_neg) and Neutral-watch-Positive (NeuW_pos). We compared the between-group variability of their responses for each condition.

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Table 1. Instructions for the continuous rating task conducted in Prolific

***Arousal**:* Click the white button (and hold it throughout) and drag it up or down depending on the intensity of emotion you feel while watching the movie, irrespective of whether you feel a positive or negative emotion.
***Valence**:* Click the white button (and hold it throughout) and drag it up or down depending on whether you feel – positive (up) or negative (down). If it gets increasingly negative, you drag it further down from the centre and vice versa.

Table 2: **Prior parameters for all simulated HGF models.**

	$\omega_1\ \mu$	$\boldsymbol{\omega_2\ \mu}$	$\omega_1\ \sigma$	$\omega_2\ \sigma$	$\boldsymbol{\theta\ \mu}$	$\theta\ \sigma$	LME
Baseline Model	99993	-8	1	0.05	2	0.05	1703
Increased Uncertainty at both levels	99993	-4	1	0.05	4	0.05	1717
Decreased Uncertainty at both levels	99993	-10	1	0.05	0	0.05	1678
Increased Uncertainty around Valence and decreased metavolatility	99993	-4	1	0.05	0.05	0.05	1737
Decreased Uncertainty around Valence, increased metavolatility	99993	-10	1	0.05	4	0.05	1497

Figure 1: Neural Variability during Naturalistic Experience shows Unique Changes in Aging. (a) Illustration depicting the regional differentiation based on neural variability across two age groups. We analysed average neural activity (μ_{BOLD}) and the neural variability (SD_{BOLD}) during movie-watching and resting state sessions in young (N=111, 18-35yrs) and older adults (N=98, 60-88 yrs). (Bottom) The illustration demonstrates that while the μ_{BOLD} and the SD_{BOLD} might be similar across age groups for ROI_1. In contrast, ROI_2 may show differing levels of SD_{BOLD} between the age groups while maintaining similar μ_{BOLD} values. This highlights that average neural activity and its variability provide distinct and complementary information about neural functioning. Main effect of (b) Movie and (c) Rest on SD_{BOLD} across young and older adults.

Posterior density estimates show significantly more evidence for increased SD_{BOLD} in old than young (P = 1, BF = 415) in movie than that in the rest (P = 0.96, BF = 21.94). (d) Main effect of movie on μ_{BOLD}. No significant difference was observed between the two groups (P = 0.83, BF = 4.89).

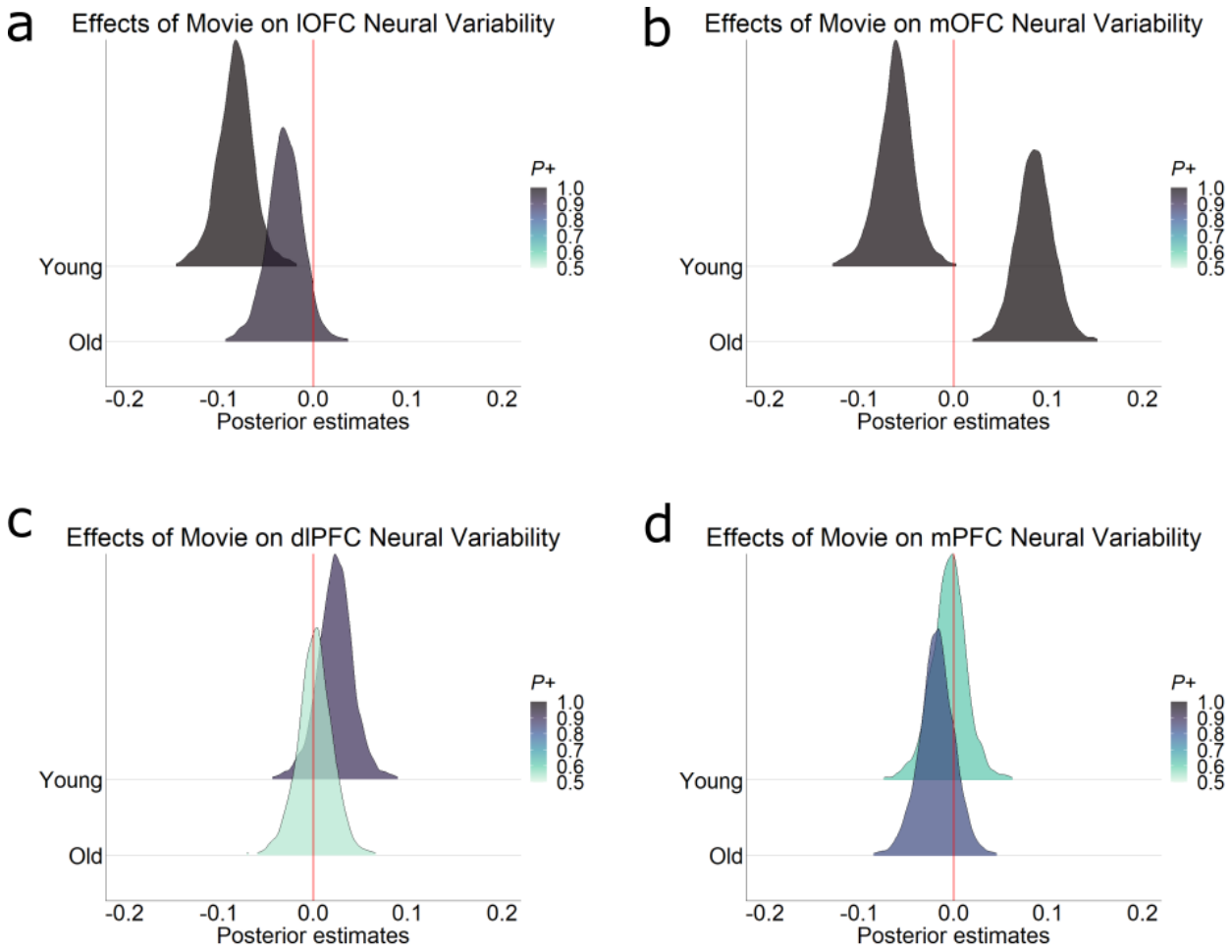


Figure 2: Neural Variability shows functionally distinct trend in the Orbitofrontal cortex in aging. ROI-level effect of the movie on the SD_{BOLD} across the two groups. (a) Posterior density estimates of lOFC shows significantly more evidence in old than young (Young: β_{mean} = -0.08, P = 0.99; Old: β_{mean} = -0.03, P = 1). (b) Posterior density estimates of mOFC also shows increased variability in old compared to younger adults (Young: β_{mean} = -0.06, P = 0.99; Old: β_{mean} = 0.08, P = 0.99). No significant differences were observed in the neural variability between the two groups for (c) the dlPFC (Young: β_{mean} = 0.02, P = 0.89; Old: β_{mean} = 0.001, P = 0.53)and (d) mPFC (Young: β_{mean} = -0.005, P = 0.61; Old: β_{mean} = -0.18, P = 0.83).

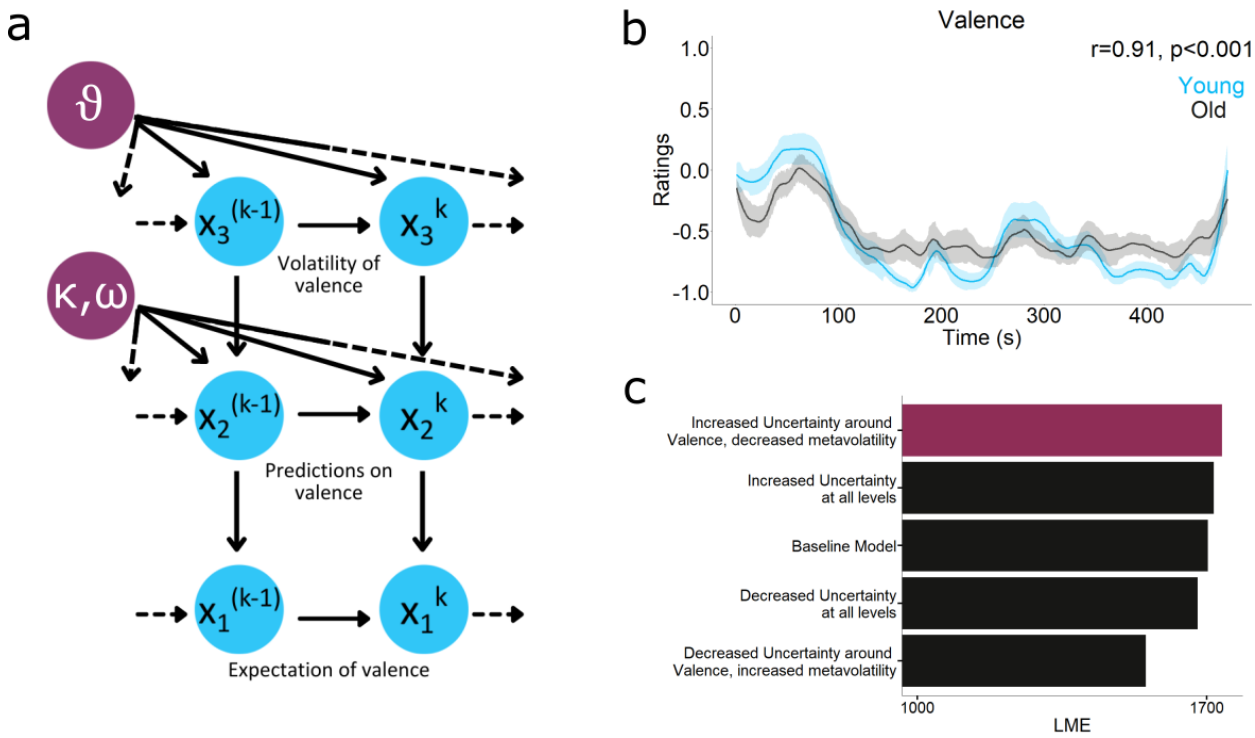
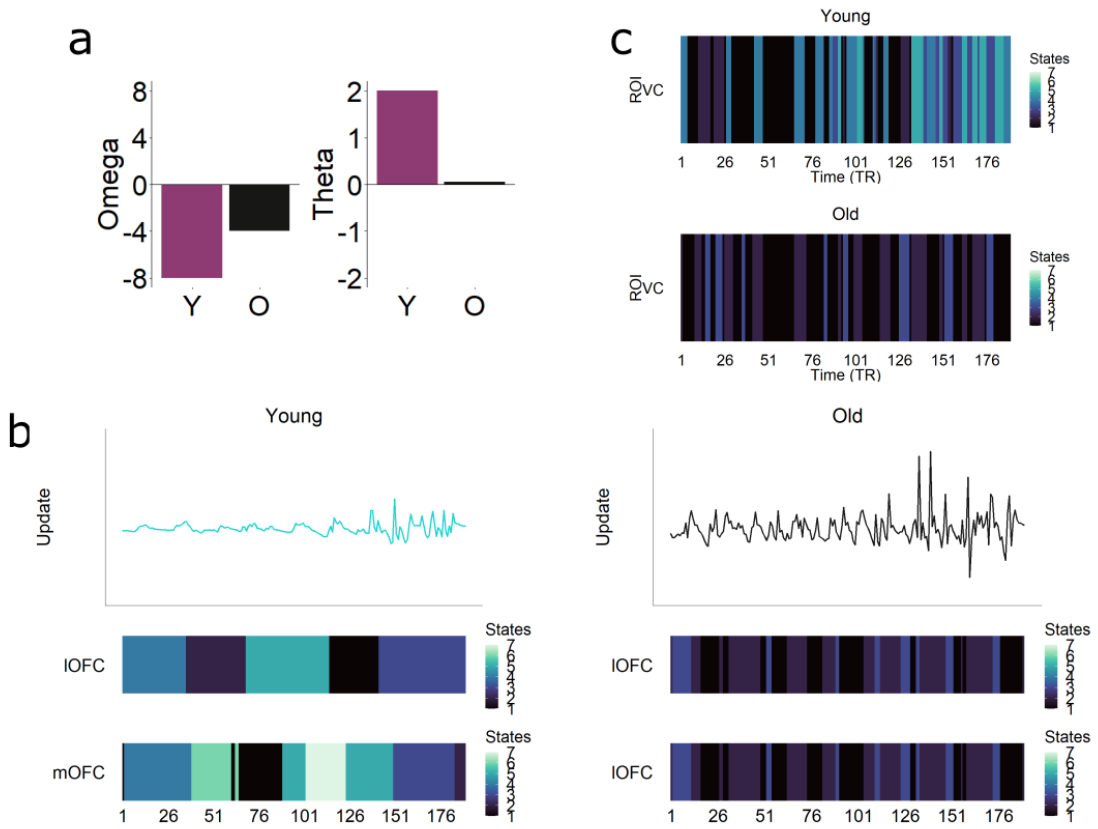


Figure 3: (a) Graphical illustration of the HGF. x_1 represents beliefs about the observed valence, which in turn is affected by x_2, representing the belief of how the valence changes. x_3 estimates the metavolatility related to the valence timecourse, which in turn affects x_2. The levels are coupled via a phasic, time-varying parameter kappa (κ). A tonic, time-invariant parameter omega (ω) influences the variance of the Gaussian walk at x_2, while theta (***ϑ***) determines the variance of the volatility. (b) Continuous ratings of Valence during the Movie in young and older adults. Older adults exhibit more variable valence than young adults although they show a strong correlation ($r=0.91$, $p<0.001$). (c) We simulated multiple 3-level HGF models for older adults and selected the models based on the highest LME. These models were simulated by lesioning two free parameters - ω and ***ϑ*** affecting the second and the third level trajectories simultaneously.



720

721 **Figure 4:** Bayesian model predictions and Orbitofrontal Neural variability in Aging. (a)
722 Parameter comparisons from the final HGF model reveal an increased ω and reduced ϑ in the
723 older adults. (b) Model prediction updates and neural state transitions of the lOFC and mOFC
724 (from HMM). Younger adults show much more stable and synchronised latent state transitions of
725 the OFC (qualitatively) which were replaced by much faster transitions in the older adults. (c)
726 The latent state transitions of the Visual Cortex (VC) between the two groups, showed a similar
727 transition pattern in both groups. This might reflect that the processing of sensory uncertainty
728 (changing of visual features) is similar in both groups.

729

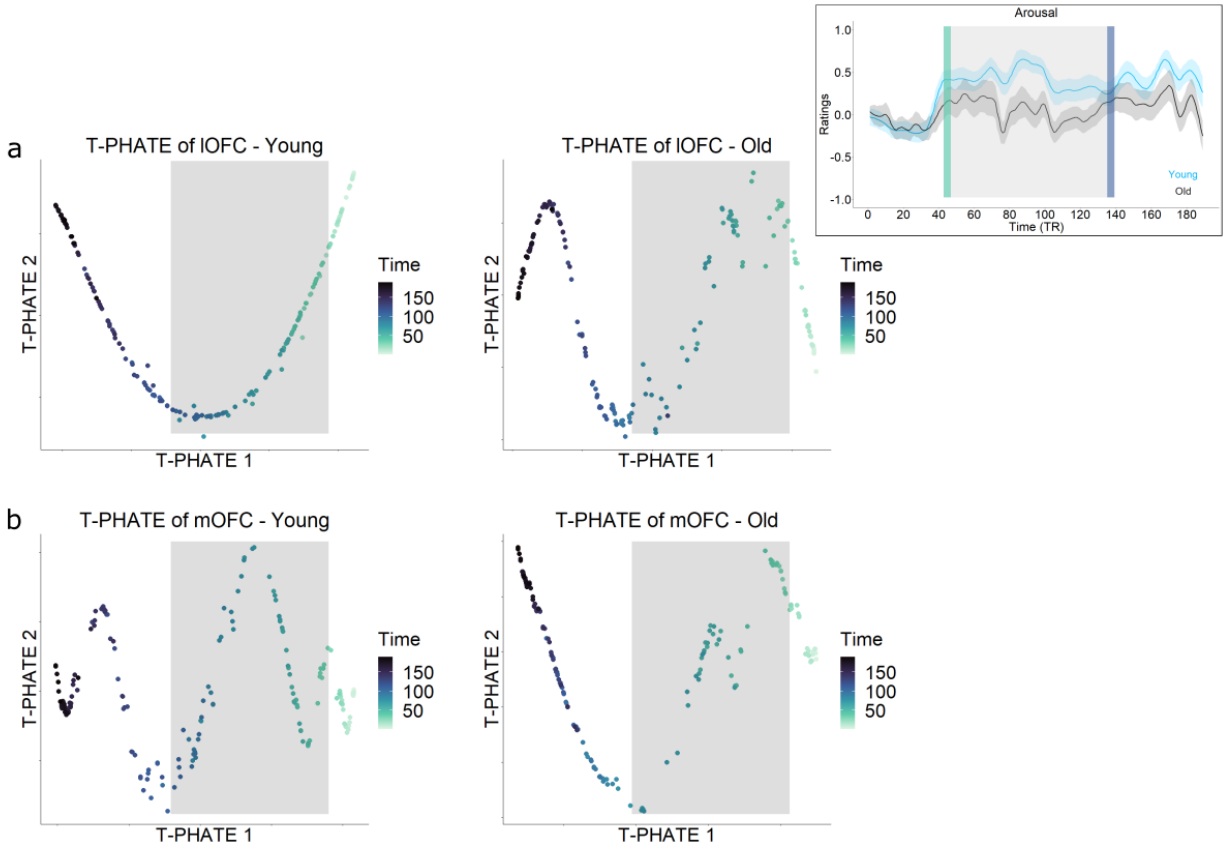


Figure 5: (inset) Older adults exhibit lower and more variable arousal ratings than younger adults (r=0.67, p<0.001). Manifold embedding of the (a) lOFC and (b) mOFC using T-PHATE. Each data point is indexed by TR. The latent temporal trajectory of both lOFC and mOFC show a conserved and sequential representation during a movie-watching task in young. In contrast, the older adults exhibit a disrupted latent trajectory, indicating alterations in their temporal dynamics in OFC especially the lOFC. Notably, the disrupted segments in their latent trajectory correspond to their differential emotional experiences during those specific parts of the movie (coloured bars in the ratings correspond to the TRs in T-PHATE embeddings). Importantly, despite the neural and behavioral data being from two independent groups of participants, a similar pattern is observed in both.

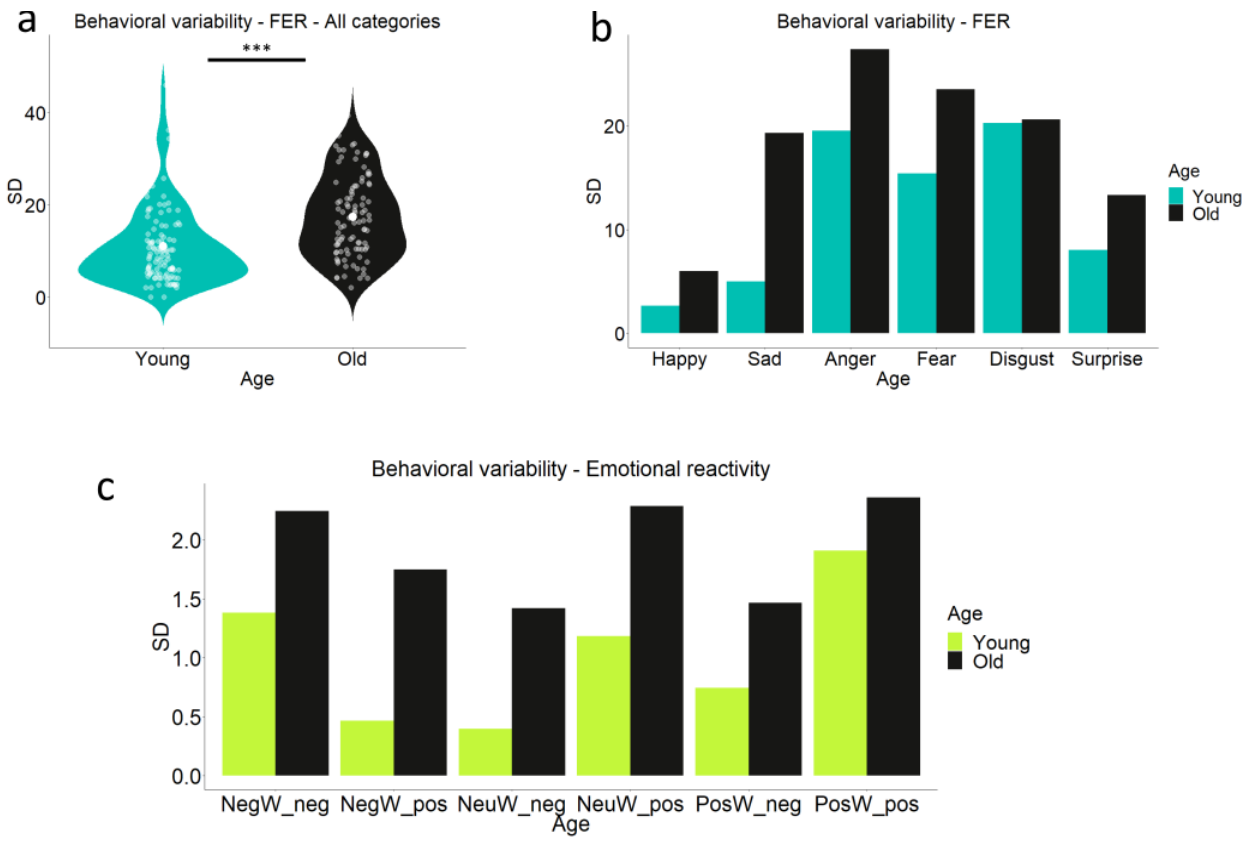


Figure 6: Generalizing age-related emotional variability to multiple tasks. (a) In the Facial Emotion Recognition (FER) task, individual variability, computed as the standard deviation (SD) of each participant's accuracy over all 6 categories depicts significantly higher behavioral variability in older adults compared to young (mean-SD_{Young} = 11.08, mean-SD_{Old} = 17.44, $P<0.0001$). (b) All emotion categories show increased variability in older adults compared to the younger individuals using between-participant SD separately for each emotion category. (c) Between-participant SD during Emotion Reappraisal task shows increased variability in behavioral responses in the old compared to young for all conditions.

Supplementary materials and methods

Bayesian Hierarchical Regression to model the effect of uncertainty and valence on the neural activity

For this analysis, we defined 5 Ascent (high-intensity scenes marked by positive arousal slopes), 5 Descent (low-intensity scenes marked by negative arousal slopes), and 1 Control (neutral scene) segments from the arousal ratings of the young in a data-driven way. Here, we employed a Bayesian hierarchical regression model to delineate the age-related effects of uncertainty and valence on emotion dynamics (Supplementary Figure 1). The dependent measure of the model input was given by the % BOLD signal for each of the 8 ROIs (mentioned in the ROI definition) for each group relative to Control and was modeled as a Student *t*-distribution:

PSC = Student $t\ (\nu, \mu, \sigma)$,

where ν is the degrees of freedom, σ is the scale parameter of the distribution, and μ is the mean, which can be expressed as:

$\mu = \alpha + \alpha_j + \alpha_i + \beta_1.\text{Age} + \beta_2.\text{Uncertainty} + \beta_3.\text{Valence} + \beta_4.\ \text{Age: Uncertainty}$

$+ \beta_5.\text{Age : Valence}$

$+ \gamma_{1j}\ \text{Age} \mid \text{ROI}$

$+\gamma_{2j}.\ \text{Uncertainty} \mid \text{ROI}$

$+\gamma_{3j}.\ \text{Valence} \mid \text{ROI}$

$+_{\gamma 4j}.\ \text{Age : Uncertainty} \mid \text{ROI}$

$+\gamma_{5j}.\ \text{Age : Valence} \mid \text{ROI}$

$+\gamma_{6j}.\ \text{Age} \mid \text{Subject}$

$+\gamma_{7j}\ .\ \text{Uncertainty} \mid \text{Subject}$

$+ \gamma_{8j}.\ \text{Valence} \mid \text{Subject} + \sigma_i + \varepsilon.$

Here, α is the intercept, α_j is the varying intercept over *j* ROIs, α_i is the varying intercept over *i* participants. β and γ reflect the slope and varying slope of the predictors, respectively. β_1 represents the slope for the age parameter (which was defined as a categorical variable -Y and O), β_2 and β_3 denote the slope for the Uncertainty and Valence respectively. β_4 and β_5 denote the slope for the cross-level interaction term of age with valence and uncertainty respectively. γ_{1j}, γ_{2j} and γ_{3j} are varying slopes where each of the 3 predictors is allowed to vary across all *j* ROIs. γ_{4j} and γ_{5j} are varying slopes for the cross-level interaction terms of age with uncertainty and valence, allowed to vary across the ROIs. γ_{6i}, γ_{7i}, and γ_{8i} are varying slopes where each of the 3 predictors is allowed to vary across all *i* (=209) participants. The way we constructed the model enabled us to consider the effect of uncertainty and valence for the two conditions (we only show the Ascent here) across

age and ROIs. Since the classification of scenes is based on the behavioral ratings of the young adults, we considered the entire movie for the main study. Here, we showed only the main effect of uncertainty and valence across age in modulating the neural activity.

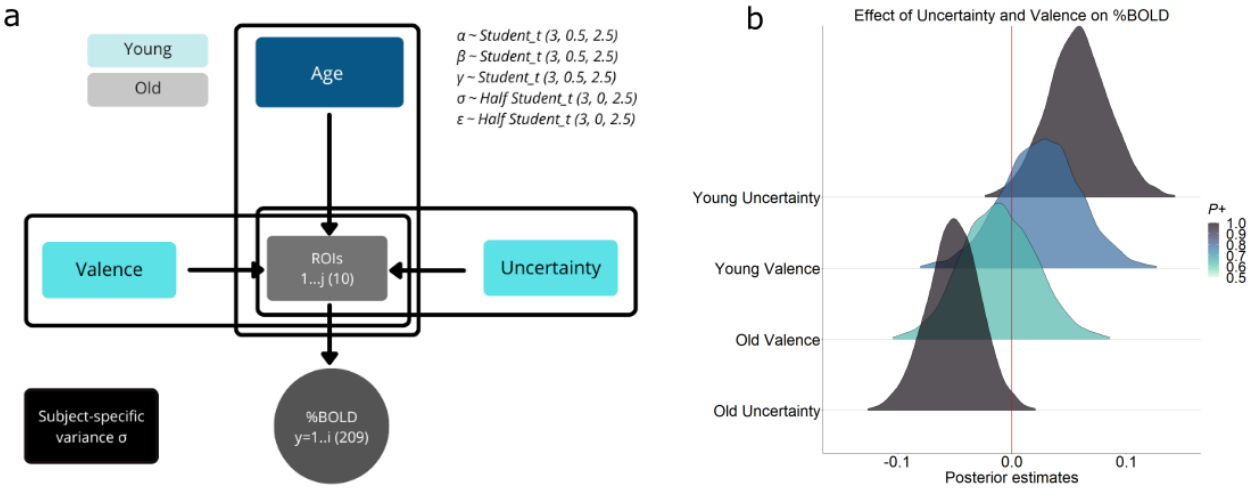


Figure S1: (a) Graphical illustration represents the architecture of the Hierarchical Bayesian model. BOLD % signal change was modeled to be drawn from a Student *t*-distribution and varied across, groups, participants and ROIs. Main effects of interest were the age-associated effect (categorically defined as Young and old) with the interaction terms of arousal (categorical predictor) with each of uncertainty and valence (as continuous predictors). (b) Main effect of Valence and Uncertainty in modulating the neural activity between the two groups. Posterior density estimates showing the effect of uncertainty is significantly difference (Young: P = 0.98; Old: P= 0.98) between the two groups compared to the valence (Young: P = 0.77; Old: P = 0.64). A potential point of critique may pertain to the stimulus classification, which is based on the ratings provided by the young participants. To address this concern, we refrained from scene categorization in our main analyses and incorporated the entire movie series for both behavioral and neural inferences.

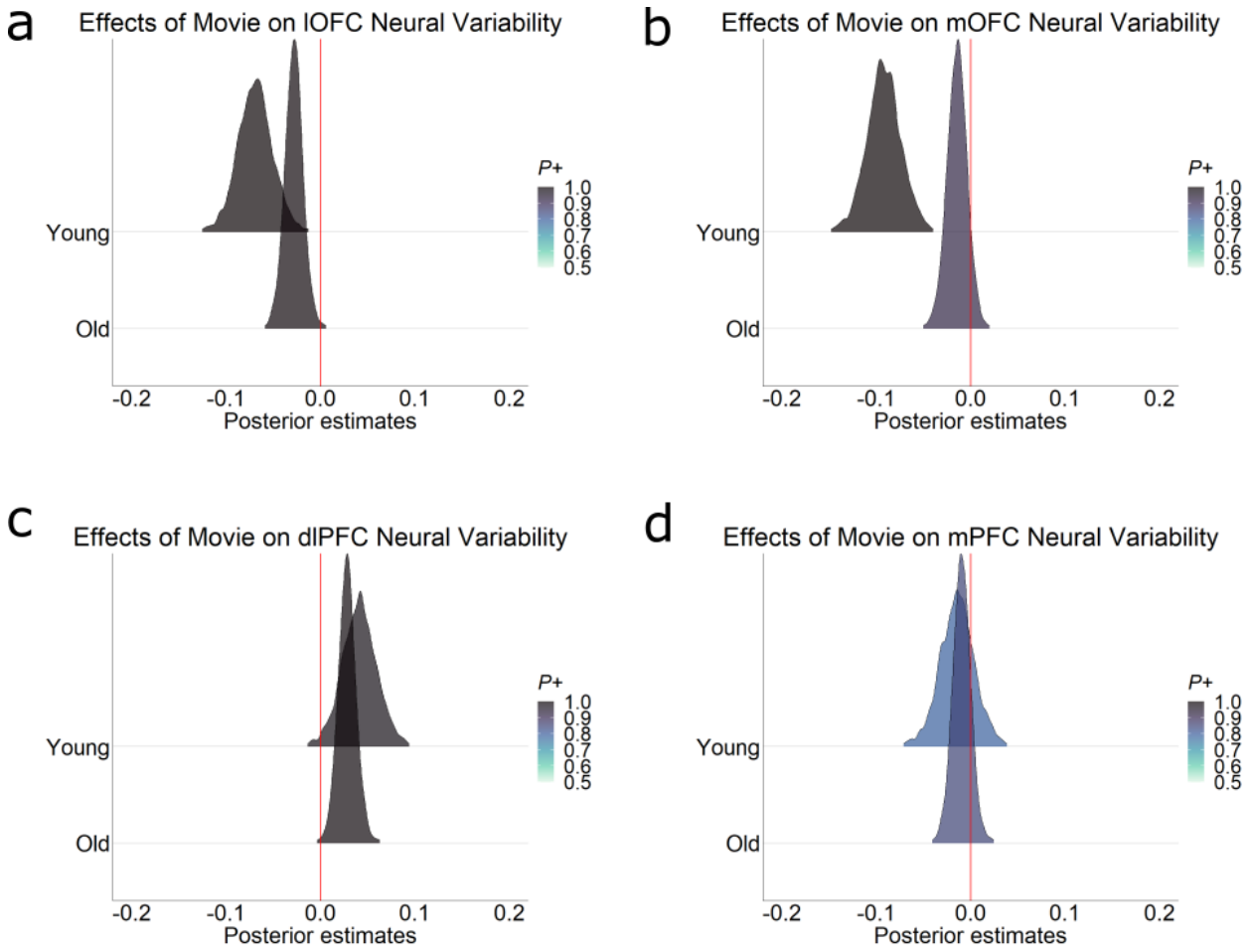


Figure S2: Neural Variability shows functionally distinct trend in the Orbitofrontal cortex in aging (with ICA-AROMA). ROI-level effect of the movie on the SD_{BOLD} across the two groups. (a) Posterior density estimates of lOFC shows significantly more evidence in old than young (Young: β_{mean} = -0.07, P = 0.9; Old: β_{mean} = -0.03, P = 0.9). (b) The posterior density estimates of mOFC showed similar pattern of increased variability in old compared to younger adults (Young: β_{mean} = -0.09, P = 1; Old: β_{mean} = -0.01, P = 0.9). No significant differences were observed in the neural variability between the two groups for (c) the dlPFC (Young: β_{mean} = 0.04, P = 0.9; Old: β_{mean} = 0.03, P = 0.9) and (d) mPFC (Young: β_{mean} = -0.01, P = 0.7; Old: β_{mean} = -0.01, P = 0.8).

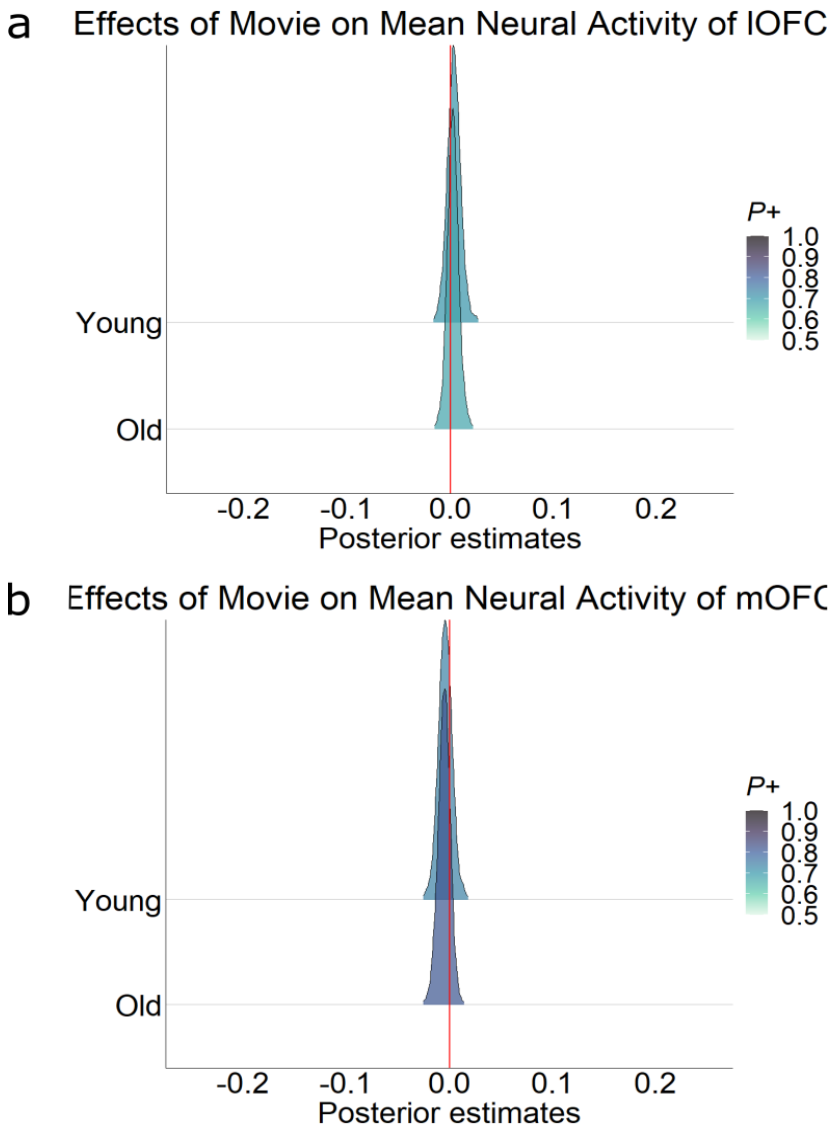


Figure S3: Mean neural activity of both lOFC and mOFC shows no significant difference between the two groups for the movie-watching task. ROI-level effect of the movie on the μ_{BOLD} (averaged BOLD signal) across the two groups. Posterior density estimates of (a) lOFC and (b) mOFC shows no significant difference between the two groups during movie.

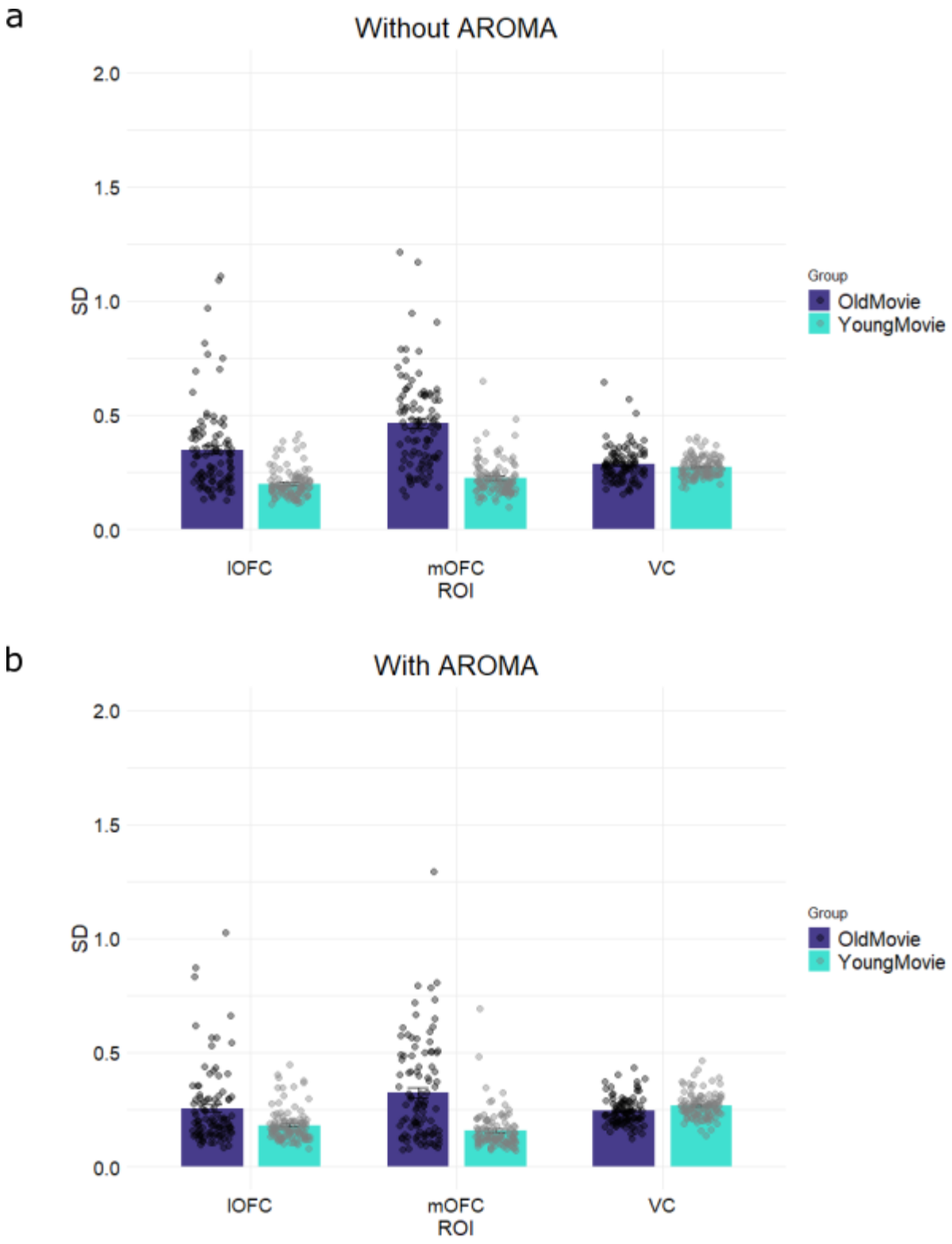


Figure S4: Comparison of the SD_{BOLD} for two separate preprocessing pipelines with and without ICA-AROMA. The lOFC and mOFC in both cases show significantly higher SD_{BOLD} in older

adults compared to young. In contrast the VC shows insignificant differences between the two groups.

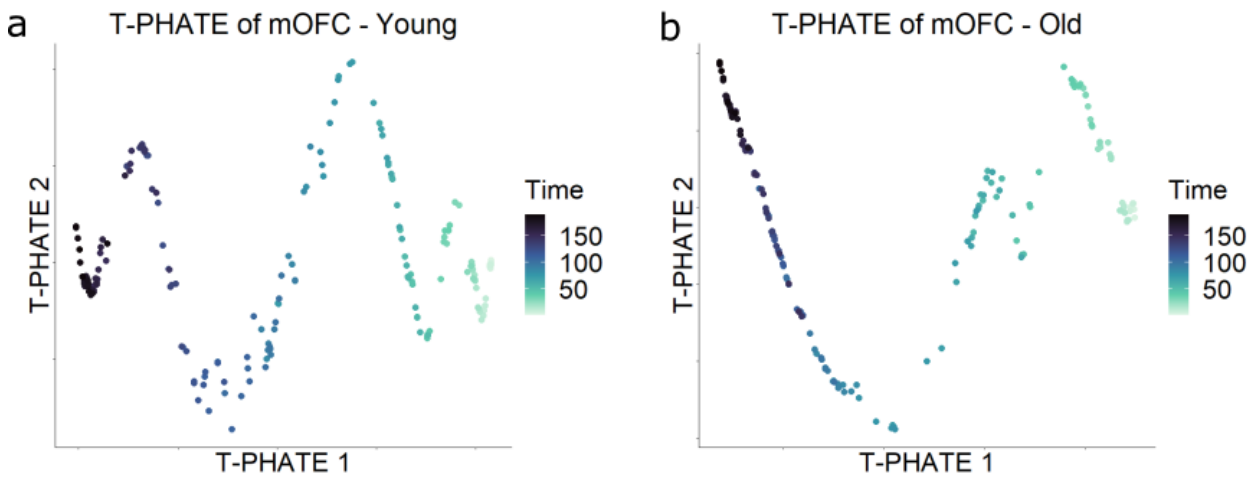


Figure S5: Latent state representations in mOFC for (a) young and (b) older individuals during the movie-watching task. Manifold embedding of mOFC show differential representational patterns in the two groups. Each dot indicates a timepoint in the movie.

Engagement analysis with whole-brain temporal intersubject correlation (ISC)

To determine whether engagement in older adults varies as a function of the emotional content of the stimulus, we performed an engagement analysis. For each condition (Ascent, Descent, and Control), we computed the whole brain temporal ISC of the older adults to compare their neural engagement with that of the Young and how it differed with the conditions. The whole-brain BOLD signal for each subject was extracted using the Power Atlas with 264 cortical and subcortical ROIs (Fig. S4).

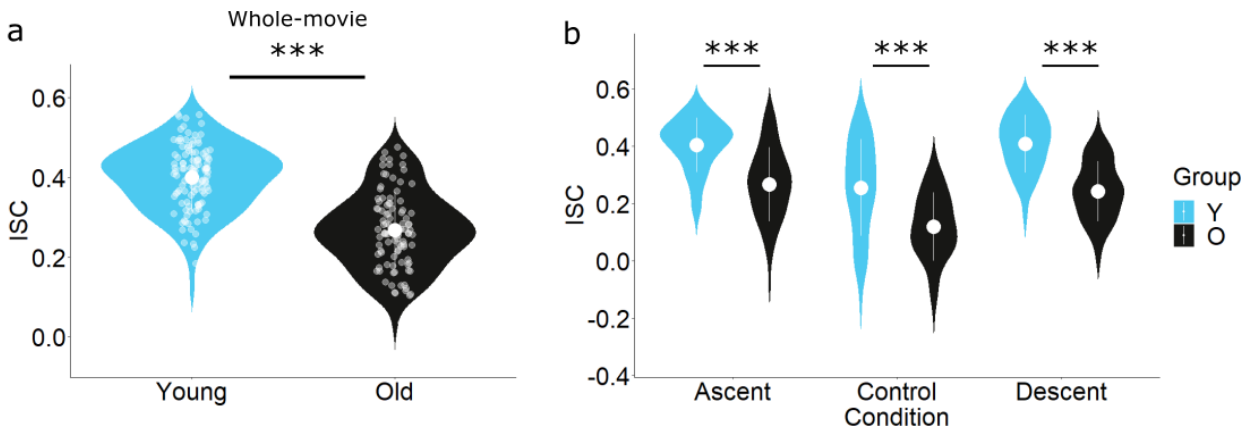


Figure S6: Shared neural engagement of Ascent, Descent and Control computed from the whole-brain ISC of the two groups. If attentional processes were the main modulators of the neural activity in the old, we would expect a lower ISC in older adults affected in a similar way for all 3 conditions, irrespective of the emotional saliency of the scenes. Whole brain temporal ISC (whole brain parcellation by Power Atlas, 264 ROIs) on the movie watching data for both groups (Y = 111; O = 98) revealed that (a) although the older individuals had lower ISC than Young for the entire movie (Young: r = 0.40; Old: r = 0.27; P < 0.0001) as well as (b) for all conditions (Ascent: Y – r = 0.41, O – r = 0.27, P < 0.0001; Descent: Y – r = 0.41, O – r = 0.24, P < 0.0001; Control: Y – r = 0.26, O – r = 0.12, P < 0.0001), within-group ISC of the old were higher for the Ascent and Descent compared to Control (similar pattern as Young). This suggests that the decreased neural engagement in the elderly varied as a function of the emotional saliency of the conditions.

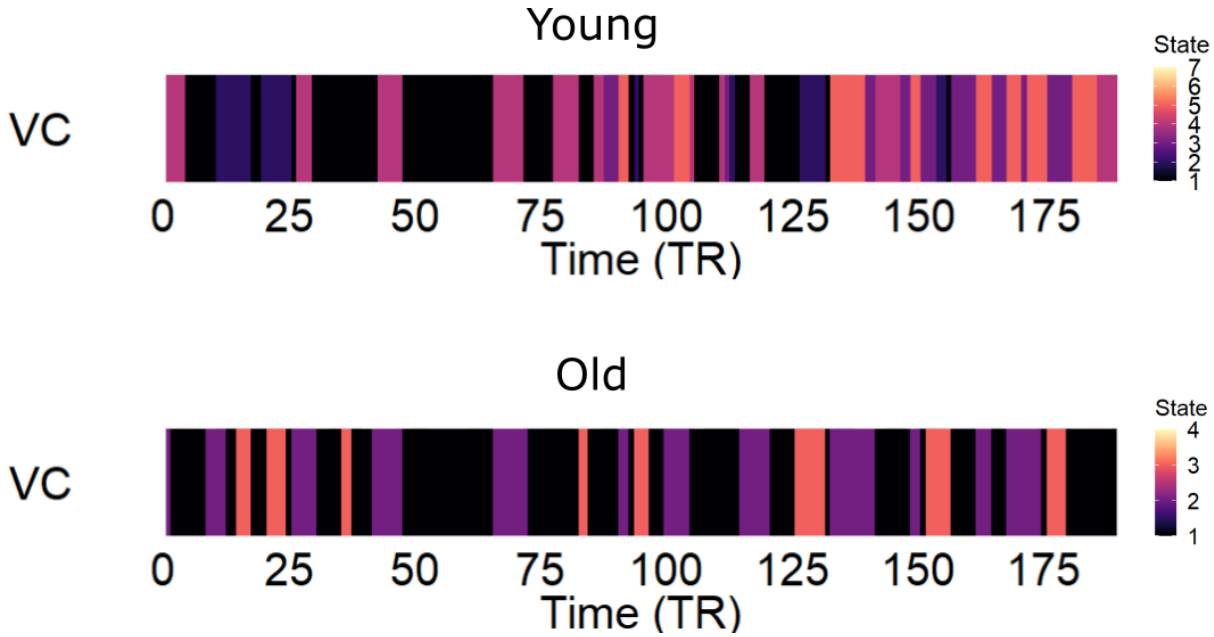


Figure S7: Comparison of the Visual Cortex (VC) HMM state transitions between the two groups showed faster transitions in both. This might reflect that the processing of sensory uncertainty (changing of visual features) is similar in both groups and cannot be attributed to the misestimation of higher-order uncertainty in the elderly.