Brain and behavioral contributions to individual choices in response to affective-cognitive persuasion

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ABSTRACT

Affective and cognitive information conveyed by persuasive stimuli is evaluated and integrated by individuals according to their behavioral predispositions. However, the neurocognitive structure that supports persuasion based on either affective or cognitive content is poorly understood. Here, we examine the neural and behavioral processes supporting choices based on affective and cognitive persuasion by integrating four information processing features: intrinsic brain connectivity, stimulus-evoked brain activity, intrinsic affective-cognitive orientation, and explicit target evaluations. We found that the intrinsic cross-network connections of a multimodal fronto-parietal network are associated with individual affective-cognitive orientation. Moreover, using a cross-validated classifier, we find that individuals' intrinsic brain-behavioral dimensions, such as affective-cognitive orientation and intrinsic brain connectivity, can predict individual choices between affective or cognitive targets. Our findings show that affective- and cognitive-based choices rely on multiple sources, including behavioral orientation, stimulus evaluation, and intrinsic functional brain architecture.

INTRODUCTION

In everyday choices, do you tend to follow emotion, reason, or both? This question recalls the classic dichotomy in psychology between affect and cognition. As applied to the psychological study of attitudes, literature has revealed that individuals differ in the extent to which they are differentially motivated to pursue and use affective and cognitive information in forming their attitudes (Maio, Haddock, & Verplanken, 2018). Many studies operationalize these predispositions via the assessment of individual differences in Need for Affect (NFA) and Need for Cognition (NFC). NFA refers to the degree to which people approach or avoid situations that are likely to induce emotion (Maio & Esses, 2001). Individuals with high NFA exhibit preferences towards emotional rather than non-emotional targets and are more likely to become involved in emotion-inducing events (Haddock & Maio, 2019). In contrast, NFC refers to the tendency to seek out and enjoy effortful cognitive activity (Cacioppo & Petty, 1982). Thus, by exploring and elaborating on information before making evaluations, individuals with high NFC are more likely to possess attitudes based on their subjective assessment of objects attributes than individuals low in NFC (Haugtvedt et al., 1992). The relative reliance on affect or cognition in attitude formation can be defined as *affective-cognitive orientation* (Aquino et al., 2020; Connor et al., 2011; Haddock & Maio, 2019) and expresses an individual's inclination toward affect or cognition.

It is well known that the correspondence between affective (i.e., the emotional attributes) or cognitive (i.e., the functional attributes) content of persuasive messages and an individual's affective-cognitive orientation enhances the effectiveness of persuasion (Fabrigar & Petty, 1999; Haddock & Huskinson, 2004; Haddock et al., 2008; Mayer & Tormala, 2010; Haddock & Maio, 2019). For example, Haddock and colleagues (2008) found that individual differences in NFA predicted greater persuasion in response to an affect-based (but not cognition-based) persuasive message about consuming a novel drink. In contrast, individual differences in NFC predicted greater persuasion in response to a cognition-based (but not affect-based) persuasive message. They referred to this correspondence as the "structural matching effect", an outcome replicated in multiple independent studies (for a review, see Haddock & Maio, 2019).

Aquino and colleagues (2020) demonstrated the involvement of the ventromedial prefrontal cortex (vmPFC), a brain region involved in persuasion (Chua et al., 2009; Falk et al., 2011; Falk & Scholz, 2018), in weighing the affective versus cognitive content of persuasive messages. Using functional magnetic resonance imaging (fMRI), they observed more robust brain activity in the vmPFC for affective (cognitive) messages among individuals with an affective (cognitive) orientation. While the findings of Aquino et al. (2020) offer novel and essential insights into the neural regions associated with the structural matching effect, we still do not know *how* individual differences in orientation are encoded by variability in intrinsic brain features, and whether such coding contributes to persuasion. Increasing evidence from graph theory (Bullmore & Sporns, 2009; Rubinov & Sporns, 2010) suggests that intrinsic brain network features measured through resting-state functional connectivity (Toro et al., 2008; Smith et al., 2009) can predict cognitive scores and personality traits (Cox et al., 2010; Di Martino et al., 2009; Di Plinio et al., 2020; Hoptman et al., 2010). Thus, investigating how brain and behavioral predispositions contribute to individual choices in response to affective-cognitive matching in persuasion would significantly improve our understanding of human behavior during persuasion.

The present study aims at understanding the neural and psychological mechanisms that support persuasion by investigating its multi-level brain-behavior coding. We combine behavioral measurements, neuroimaging data, and machine learning to investigate persuasive matching beyond the unique lens of behavior. First, we ask whether intrinsic brain functional connectivity patterns may support individual intrinsic orientation. In other words, we assess if the functional brain architecture predisposes individuals' tendencies to differentially approach affective and cognitive activities and information. Second, we investigate whether such intrinsic brain-behavior features predispose individuals to choose between items introduced by affective or cognitive persuasive messages.

For these purposes, we adopt a multimodal persuasion experiment incorporating individual differences in intrinsic (resting state) brain connectivity, extrinsic (task evoked) brain activity, intrinsic behavioral orientation (NFA/NFC), extrinsic behavioral evaluations, and choices. **We clarify that the term "choice" in this context refers to the individual's *preference* for a product described by an affective persuasive message rather than by a cognitive one (or vice versa).** We employ machine learning classification techniques to test the contributions of behavioral and brain data to individual choices. In particular, we analyze whether and how brain-behavioral features predict whether an individual is more likely to choose a target introduced by an affective or cognitive persuasive message. Moreover, we test whether intrinsic information (i.e., connectivity and orientation) strengthens the prediction of choices, compared to individuals' extrinsic evaluations.

Given the relative specialization of the right hemisphere in the elaboration of emotional stimuli (see Killgore & Yurgelun-Todd, 2007; Schwartz et al., 1975) and the involvement of the left hemisphere in sentence elaboration (Geschwind, 1972; Sakai et al., 2005), we hypothesize individual differences in orientation to be associated with cross-hemispheric asymmetries in intrinsic functional connectivity. Such asymmetries may reflect a differential elaboration of affective versus cognitive information, putatively representing an intrinsic neural background of the structural matching effect.

Moreover, intrinsic functional connectivity can predict behavioral variability and predispositions towards certain behaviors, such as sedentary behavior (Cooper et al., 2017). Such complex neurocognitive processes and behaviors may arise from mechanisms of integration and segregation of brain subsystems (Ito et al., 2019; Di Plinio et al., 2020). Therefore, we also expect that information about affective-cognitive orientation and intrinsic brain indices of network integration and segregation may significantly contribute to the prediction of individual choices between products introduced by affective or cognitive messages.

MATERIALS AND METHODS

Participants and Dataset

Thirty-five healthy Italian adults (20 women and 15 men, aged 25.2 ± 3.4 years) without a history of psychiatric or neurological disease and contraindications for MRI scanning participated in the experiment. All participants were right-handed. The local ethics committee approved the study. All participants had a normal or corrected-to-normal vision and provided written informed consent before participating in the study following the Declaration of Helsinki (2013).

The participants in this study were from Aquino et al. (2020). Notably, while Aquino et al. (2020) analyzed only task-related data to study the evoked-activity brain correlates of the structural matching effect, in the present study, we included a slightly higher number of participants, and treated both resting-state and task-evoked fMRI data. We investigated a combination of brain and behavioral measures to study the neural basis of affective-cognitive orientation and their contribution to individual choices in response to affective and cognitive persuasive messages.

The workflow of the experiment is illustrated in Figure 1.

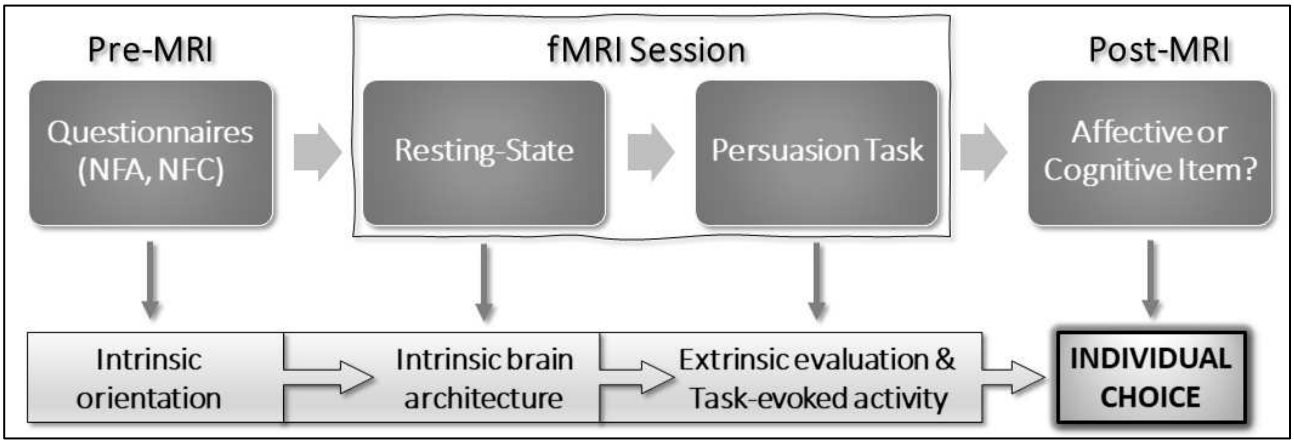

Figure 1. Schematic illustration of the experimental paradigm. Participants' NFA and NFC were assessed with the short version of the NFA scale (NFA, Appel et al., 2012) and the 18-item NFC scale (NFC, Cacioppo et al., 1984). NFA and NFC were also used to calculate orientation (intrinsic behavioral trait). In the scanner, participants underwent both resting-state and task runs. The two resting-state runs were analysed using graph theory principles to recover the brain's functional architectures (intrinsic brain trait). During the persuasion task, both behavioral and

neurophysiological data were acquired. Participants' behavioral attitude and intentions were used to calculate evaluations of the items introduced by affective messages (Affective Evaluation) and of the items introduced by cognitive messages (Cognitive Evaluation). These two variables were used to calculate the compound variable Evaluation (extrinsic behavioral trait). Task-evoked single-trials basis (Pessoa & Padmala, 2007; Chen et al., 2021). After the MRI scanning, we asked participants to re-read the persuasive messages presented during the task. Participants expressed their choice between the items introduced by affective or cognitive messages through a 7-point Likert scale. This final variable was labeled choice **indicating the individual's preference for a product introduced by an affective/cognitive message**.

Stimulus Development

As in Aquino et al. (2020), affective and cognitive persuasive messages presented in the MRI scanner were chosen following a strict preliminary procedure. First, 20 affective and 20 cognitive messages describing consumer products (e.g., a book) were created based upon real advertisements. An affect-based and cognition-based advertising message was generated for each product. Each message contained five written sentences, similar to those used by Falk and colleagues (2011). The affective statements included terms regarding feelings and sensations induced by the product (e.g., "*The soft wool of the pullover 'Tender' gives a fresh scent all day*"). In contrast, the cognitive statements described the product's features and qualities (e.g., "*The new full-resistant pullover is made with 100% merino wool*"). Messages were built to elicit positive reactions to avoid any possible confound with valence.

The 40 persuasive messages were pre-tested by asking 64 participants (58 females, 6 males; mean age = 22.0 ± 3.1 years old) to evaluate each message on its affective-cognitive content (1 = very affective, 6 = very cognitive) and its credibility (1 = not at all credible, 6 = very credible). Messages with self-references were administered to half of our participants (e.g., "The pullover Tender cuddles you in a warm hug"), and messages without self-references the other half (e.g., "The pullover Tender cuddles who wears it in a warm hug") to exclude biases related to self-relevance in the perception of the affective/cognitive content. A mixed-effects ANOVA including a between-subject factor (two levels: self-references, non-self-references) and a within-subject factor (two levels: affective, cognitive) showed a significant interaction effect ($F_{(1, 62)} = 5.0$, $p = .029$). The analysis of simple main effects showed that the difference in the perceived affective and cognitive content was stronger for self-referred messages ($M_{AFF} - M_{COG} = 1.42$; $F_{(1, 62)} = 86.3$, $p < .001$, 95% confidence intervals (CIs) for the mean difference [1.11, 1.72], $\eta^2 = .58$), than for non-self-referred messages ($M_{AFF} - M_{COG} = 0.95$; $F_{(1, 62)} = 44.0$, $p < .001$, 95% CIs for the mean difference [0.66, 1.23], $\eta^2 = .41$). Since these results highlight the importance of self-references in the accentuation of affective–cognitive perception differences, we selected the 10 affective and 10 cognitive self-referring messages that differentiated most strongly affective versus cognitive quality perception based on paired t-tests. Importantly, target messages differed on affective versus cognitive content ($t_{(31)} = 12.0$, $p < .001$,

$M_{AFF} - M_{COG} = 1.49$, 95% CIs for the mean difference [1.25, 1.73], Cohen's $d = 1.49$), but they did not differ in credibility ($t_{(31)} = 1.44$, $p = .154$, $M_{AFF} - M_{COG} = -.07$, 95% CIs for the mean difference [−.17, .03], Cohen's $d = .18$). The affective and cognitive messages did not differ in total length as indexed by the average number of words, ($t_{(9)} = 0.1$, $p = .918$, $M_{AFF} - M_{COG} = 0.50$, 95% CIs for the mean difference [−10.2, 11.2], Cohen's $d = .18$).

To further ensure the appropriateness of this subset of 20 messages, they were rated by 22 new participants. The analyses of the ratings confirmed a strong differentiation in the perception of affective–cognitive content ($t_{(21)} = 6.09$, $p < .001$, $M_{AFF} - M_{COG} = 1.64$, 95% CIs for the mean difference [1.11, 2.17], Cohen's $d = 1.30$). The results also indicated that the affective and cognitive messages were rated as equally credible ($t_{(21)} = 1.54$, $p = .137$, $M_{AFF} - M_{COG} = -.19$, 95% CIs for the mean difference [−.43, .05], Cohen's $d = .30$). Finally, to control for the duration of the presentation of each persuasive message, each message was vocally registered at a normal pace. Subsequently, we presented ten new participants with all audio messages to ascertain that the timing was sufficient to read and understand the messages. The time employed to read the stimuli did not differ between the affective (36.2 ± 6.1 seconds) and cognitive (37.8 ± 4.8 seconds) messages ($t_{(19)} = -1.17$, $p = .271$, 95% CIs for the mean difference [−4.7, 1.5], Cohen's $d = .26$).

Pre-MRI Behavioral Measures

As reported in Aquino et al. (2020), before fMRI scanning, we assessed participants' levels of need for affect (NFA) and need for cognition (NFC). Participants' NFA was assessed with the short version of the NFA scale (Appel et al., 2012). This scale comprises ten items: five items measure the motivation to approach emotions (e.g., "Emotions help people to get along in life" $\alpha = .83$) and five items assess the motivation to avoid emotions (e.g., "I do not know how to handle my emotions, so I avoid them" $\alpha = .81$). Participants responded to these statements on a 7-point scale (1 = totally disagree; 7 = totally agree). The individual NFA score was calculated by summing responses after reverse-scoring avoidance items (average score ± standard deviation, SD = 5.52 ± 0.68, range of observed scores [4.10, 6.50]). Participants' NFC was assessed using the 18-item NFC scale (Cacioppo et al., 1984). Participants rated the extent to which they agreed with items such as "I really enjoy a task that involves coming up with new solutions to problems" and "Thinking is not my idea of fun" (reverse scored). Participants responded to these statements on a 7-point scale (1 = extremely uncharacteristic of me; 7 = extremely characteristic of me). The NFC score was calculated by summing responses after reverse scoring the negatively keyed items (average score = 4.95 ± 0.58, range of observed scores [3.50, 6.00]).

For both conceptual and methodological reasons, we operationalized the personal orientation of the participants as the difference between standardized NFA and NFC scores (orientation = NFA – NFC), such that a higher score reflects an affective orientation. From a conceptual perspective, we were interested in examining the relative reliance on affect versus cognition (see also Aquino et al., 2016). From a methodological perspective, conceptualizing individual differences in the form of a difference score strengthens the interpretability of the analyses (Rogosa & Willett, 1983; Furr, 2011; Gollwitzer et al., 2014; Mattes & Roheger, 2020). It also leads to appropriate statistical-mathematical modeling, including more degrees of freedom in error terms. Thus, a higher orientation score indicated a higher reliance on affect, whereas a lower score indicated a higher reliance on cognition. Since the compound variable "orientation" may be considered an approximation of NFA and NFC "original" variables, we also performed additional supplemental analyses using NFA and NFC scales separately. **To note, the two original scores of NFA and NFC exhibited a moderate positive correlation (r=0.43).** The parallel investigation of these factors would help interpret the results to know how participants' responses were predicted by the scales individually or interactively. The metric orientation (together with NFA and NFC) represents the *intrinsic feature of the behavior* in our study (Figure 1).

MRI Data Acquisition

As reported in Aquino et al. (2020), imaging data were acquired using a 3 Tesla MR scanner (Philips Achieva X Series; Philips Medical System, Best, The Netherlands) at the Institute of Advanced Biomedical Technologies (ITAB) in Chieti, Italy. A sensitivity-encoding eight-channel brain coil was used. Head motion was minimized using foam padding and surgical tape. A response pad was fixed in place using surgical tape connected to the scanner bed allowing the keypress with the right index and right middle fingers to interact with the ongoing task. An initial T1-weighted anatomical (3-D TFE pulse sequence) was acquired with the following parameters: field of view = 240 mm; voxel size = 1mm^3; TR = 8.1 ms; TE = 3.7 ms. Subsequently, two resting state run (234 volumes for each run) and two task fMRI runs (404 and 397 volumes, respectively) were acquired using a T2* weighted EPI sequence with TR = 1.8 s; TE = 30 ms; number of slices = 35; slice thickness = 3.5 mm; in-plane voxel size = 3 mm^2; field of view = 228 × 122 × 240 mm; flip angle = 85°.

MRI Experimental Procedure

After the assessment of NFA and NFC, all participants underwent the fMRI scan session. Neural activity was monitored both during resting-state (task-free) periods and during the execution of a persuasion task. Two resting-state fMRI runs (6 min each) were recorded during which participants were instructed to watch a white fixation cross presented on a black screen while keeping their eyes open (they were monitored through a video camera placed in the MRI room). During the task, participants were visually presented with the affective and cognitive persuasive messages for each object (example of an affective message for a backpack: "*Choosing the Backpack 'Poke' makes you feel all the potentialities of life in a joyful party of colors and makes you feel the excitement of a new journey where every direction is possible. 'Poke' marks the rhythm of the most exciting experiences of your life and does it with overwhelming energy. 'Poke' also offers endless possibilities to express your personality and to be surprised by unique and innovative solutions. Over the years, it has become a symbol of discovery, euphoria, and freedom for all generations. 'Poke' is a real icon of contemporary style, with an exciting story to tell*"; example of a cognitive message for a backpack: "*The 'Caps' backpack is very handy and comfortable thanks to the many internal pockets that allow you to carry everything you need. Its dimensions allow you to carry it as hand luggage on all main airlines. The 'Caps' backpack is also equipped with a very useful inner lining that protects your notebook from hits and rain. Ergonomic shoulder bag and filled seatback make it one of the most comfortable backpacks on the market. 'Caps' shows an original front closure with leather strips, and it is also equipped with a hidden magnet closure*"). Participants were informed that during the scan session they would be asked to read 20 messages and that subsequently they would be asked to evaluate each target presented in the messages. The affective and the cognitive messages were presented in a randomized order in two fMRI runs. During the reading phase, participants were asked to read each message attentively. The duration for the reading phase was set based on the pre-test to ascertain that the time for the reading was sufficient for participants. After MRI, participants reported being able to read all the messages.

An explicit evaluation phase always followed the reading phase: after a randomly varying interval (1.8 to 5.4 seconds), participants expressed their attitude by rating how much they liked the object, on a scale ranging from 1 (not at all) to 7 (very much). In addition, after another randomly varying interval (1.8 to 5.4 seconds), we assessed intentions to buy the described object by asking participants how likely it was that they would buy the object in the following three weeks on a scale ranging from 1 (not at all) to 7 (very likely). Participants reported attitude and intention ratings after each message. Participants expressed their answers by pressing buttons that allowed them to increase (button press with the right middle finger) or decrease (button press with right index finger) the score starting from a value of 4 that appeared on the screen (minimum = 1, maximum = 7). All participants had a time limit of 5.4 seconds to express their attitudes and intentions. Given the high correlation between attitudes and intentions ($r = .96$, $p < .001$), these judgments were averaged to create unique indexes labelled Affective Evaluation and Cognitive Evaluation. As we did for the variable orientation, we performed analyses using both the difference score (Evaluation = Affective

Evaluation – Cognitive Evaluation) and the separate affect and cognition scores. The *Evaluation* metrics represent the *extrinsic features of behavior* in our study (Figure 1).

MRI Data Preprocessing

Preprocessing and the analysis of functional images were implemented through the software AFNI (Analysis of Functional Neuroimages, web link; Cox, 1996). Functional images were deobliqued, despiked, and corrected for time-shifted acquisition. A six-parameter motion-correction and body realignment was applied before realigning the functional images to the Montreal Neurological Institute standard brain (MNI) using nonlinear warping. Motion parameters were stored during the preprocessing to further correct for motion correction during the following analysis. The functional images were scaled to have voxels with an average value of 100, which allows to translate the (unitless) BOLD signal to "percent of signal change", that has been frequently used as it is a more interpretable index (Chen et al., 2017). The functional images were spatially smoothed using a Gaussian filter of 5-mm FWHM.

Task runs were additionally analyzed by implementing a generalized linear model (GLM) at the single-subject level to estimate brain evoked activity during the affective and cognitive conditions of the task. The GLM was implemented in AFNI and included two regressors of interest representing the *affective* and *cognitive* experimental conditions which were modeled with duration-modulated BLOCK functions. The duration of the BLOCK function for each trial corresponded to the duration calculated for each target during the pilot experiments. Keypresses for target evaluations were modelled through separate regressors using GAM functions. Each GLM also included the following regressors of no-interest: six-parameters motion regressors, cerebrospinal fluid signal, white matter signal, linear and non-linear drifts. Once the brain activity was estimated in each experimental condition, we calculated the difference $\Delta\beta_{A-C} = \beta_A - \beta_C$, where β_A is the value for the regressor Affective and β_C is the value for the regressor Cognitive. Thus, the term $\Delta\beta_{A-C}$ represented the difference in evoked activity between affective and cognitive persuasive stimulation and was used in later analysis steps. We also adopted a single-trial modelling of brain activity (Pessoa & Padmala, 2007; Chen et al., 2021) to allow the extraction of $\Delta\beta i_{A-C}$ related to each target *i* to gather trial-level information to be implemented in machine learning models (see below). The metric of (differential) task-evoked activity represents the *extrinsic feature of the brain* in our study.

With respect to the resting-state runs, and in line with current guidelines (Power et al., 2014), time series were additionally censored by removing volumes with 10% or more motion outliers across voxels and volumes with Euclidean norm of the motion derivative exceeding 0.2 mm. A band-pass filter (frequency interval: 0.01 – 0.10 Hz) was applied in the same regression step that implemented censoring (Caballero-Gaudes & Reynolds, 2017). To maximize signal-to-noise ratio, motion parameters were included in the regression as noise covariates together with the signals extracted from white matter and cerebrospinal fluid. We did not regress out the global signal because it is a controversial approach (Saad et al., 2012), and because it has been shown that it introduces spurious negative correlations (Weissenbacher et al., 2009).

Connectomics

Resting-state runs allowed the extraction of modular structures (brain functional networks) and graph indices from functional connectivity matrices. Graph nodes were obtained by combining cortical and subcortical parcellations (386 nodes) from Joliot and colleagues (2015) with the cerebellar atlas (32 nodes) from Diedrichsen and colleagues (2009). Functional connectivity among each couple of nodes was calculated using the z Fisher transform of the Pearson correlation among average time series extracted from the voxels within each node after preprocessing. A binary graph was built for each participant after thresholding (the top 10% stronger connections were maintained). Functions and algorithms from the Brain Connectivity Toolbox (BCT, Rubinov & Sporns, 2010) were adopted in MatLab (The Mathworks, version 2019b) to estimate modular structures. The resulting brain architectures were visualized using BrainNet Viewer (Xia, Wang, & He, 2013). The robust Louvain algorithm (Lancichinetti & Fortunato, 2009) was used to find optimal community (modular) structures through modularity maximization (Porter et al., 2009) and following an iterative fine-tuning process (Sun, et al., 2009) created to handle the stochastic nature of the Louvain algorithm (Bassett et al., 2011). The agreement matrix, that is, the matrix whose elements represented the number of times two nodes were assigned to the same module across participants, was used to estimate group-level modular structures using a community detection algorithm developed for the analysis of complex networks (Lancichinetti & Fortunato, 2012), with the number of repetitions set to 1000. As already pointed out in methodological papers (Betzel et al., 2017), the structural resolution parameter γ (i.e., the weight of the null model in the estimation of the brain architecture) plays an important role in network analysis. To avoid biases, we investigated all the possible γ values in the interval [0.3 – 5.0]. The Newman–Girvan procedure was employed to detect significant modules in the consensus structure (Newman & Girvan, 2004). Once the modular structures were defined, graph metrics describing the nodal connectional profile in terms of network integration and segregation were extracted from each node. These metrics were the participation coefficient (i.e., the strength of inter-modular connections of a node) and the within-module degree (i.e., the strength of intra-modular connections of a node). To allow a comprehensive interpretation of brain-behavior associations, group analysis that investigated the relationships between graph indices and behavioral measures were performed at the network level for each module detected with each value of γ. Metrics of participation and within-module degree represent the *intrinsic features of the brain* in our study (Figure 1).

Post-MRI measures

We asked participants to re-read the persuasive messages presented during the previous fMRI task at the end of the fMRI scanning section and outside the scanner. For each pair of messages (i.e., for each item type) participants read the sentence "*If you had to choose only one *item type*, which one between [name of the affective item] and [name of the cognitive item] will you choose?*". Participants expressed their choice between the items introduced by affective and cognitive messages through a 7-point Likert scale (1 = "*absolutely [name of the affective item]",* 7 = "*absolutely [name of the cognitive item]"*). The affective-cognitive anchors' position (left/right) was balanced across objects and participants. Participants operated such a choice for each of the ten targets used in our experimental fMRI study. The order of presentation of the stimuli was randomized across participants. **As mentioned above, the label "choice" indicates the relative preference to select a product presented by the affective persuasive message rather than by the cognitive one, or vice versa**.

Analysis of Intrinsic Brain-Behavior Relationships

Resting-state neural correlates of affective-cognitive orientation were assessed using mixed-effects regression models, and separate analyses were implemented for participation coefficients and within-module degrees. The dependent variable was one of the graph measures of interest, and the subjective orientation was the continuous regressor of interest. Random effects were included as random intercepts at both the subject and nodal levels. Furthermore, a random slope for orientation was added at the nodal level to allow precise, node-specific modeling of brain-behavior relationships. The same analyses were implemented using original NFA and NFC scores separately to obtain more detailed insights into the brain coding of behavior. Regressions were performed independently to detect module-specific associations between network measures and orientation. Only modules significant after the Newman-Girvan procedure were analyzed. After model diagnostics and outlier removal, results were corrected for multiple comparisons using false discovery rate (FDR) across the total number of significant modules. Best linear unbiased predictors (BLUPs) were extracted to estimate effects at the nodal level and highlight nodes with the highest contributions (Liu et al., 2008). Individual conditional expectation (ICE) plots were generated to visualize significant effects across random groupings (Goldstein et al., 2015). For significant associations, to ease the representation of results, a cross-γ linear mixed-effects regression was modeled using γ as a different random grouping factor. We report statistics of the cross-γ model in the text of the Results section and statistics related to single γ values in the figures.

Predictions of individual choices using machine-learning.

We assessed if intrinsic and extrinsic features can predict individual choices (i.e., the individual's relative preference towards an item introduced by the affective or cognitive message). In other words, we studied if such features predicted if the individual would select the product introduced by an affective message or the (same) one presented by a cognitive message. In addition, we tested whether intrinsic information (i.e., connectivity and orientation) improved the prediction of individual choices compared to the prediction performance of extrinsic information alone (i.e., task-evoked activity and behavioral evaluations). We implemented a semi-automated machine learning modeling procedure using a binary classifier to accomplish this aim. To allow the application of a binary classifier, choices from 1 to 3 (1, 2, or 3) were labeled as «Cognitive» (the individual would like to choose the cognitive target, rather than the affective one) and choices from 5 to 7 (5, 6, or 7) were labeled as «Affective», where with "choice" we refer to the individual's decision to pick the product presented by the affective persuasive message rather than by the cognitive one, or vice versa. Trials with intermediate ratings, that is, in which the score was equal to 4, were not frequent and were excluded from the analysis (average: 1 trial per subject; range [0, 2]). After the binarization of the behavioral choice, a linear support vector machine (SVM) with k-fold cross validation was employed. The SVM works by selecting the hyperplane that best separates the two classes (i.e., Affective choices versus Cognitive choices) across all the features in the training sample. Then, the same hyperplane is applied as the criteria for predicting the outcome in the test sample. The accuracy of the classifier was calculated as the proportion of successfully predicted targets in the test sample, averaged across the *k* repetitions (and the number of repetitions of the algorithm). Predictor importance scores for each classification were extracted using the minimum redundancy maximum relevance algorithm (Ding & Peng 2005). The combination of feature selection, predictor importance, and different classification models allowed to comprehensively assess how different brain and behavioral features predicted choices.

Since we started from multiple features, we implemented a semi-automated algorithm for selecting the best predictors of individual choices. Automated machine learning procedures enable to build accurate machine learning models faster by performing feature engineering, algorithm selection, and tuning as well as documenting the model performance (Serra et al., 2018; Hutter et al., 2019). **In our dataset, we wanted to predict the binary relative choice of the Affective versus Cognitive target starting from a set of variables including orientation (intrinsic behavior term),**

Evaluation (extrinsic behavior term), nodal participation coefficient (intrinsic brain term) and brain activity (extrinsic brain term). To perform automated variable selection, the SVM classifier was trained with every possible combination of the four starting sets of variables (15 total combinations). Then, the variables which did not significantly improve the classification efficiency were gradually excluded by comparing efficiency scores across 100 repetitions until the selection of an ultimate model. With respect to brain data, in order to avoid overfitting and information redundancy, a further step of feature selection was performed before the application of the SVM algorithm by adopting a conditional distribution approach (Cai et al., 2018): the difference between the brain parameter (participation coefficient) in the two pooled choice conditions (Affective choices versus Cognitive choices) was calculated across targets for each node, and then relevant brain features were selected as these brain nodes for which the effect size was large enough to allow significance in a two-sample t-test ($p<.05$, FDR corrected). Since the dichotomization may imply partial loss of information (Mariooryad & Busso, 2017), we ran a parallel analysis employing an ordinal classifier to predict individual choices and confirm results from the binary classifier. The application of an ordinal classifier on an ordinal scale is more appropriate than regression as a control analysis and avoids both dichotomization and eventual exclusion of partial data,

The cross-validation of the classifiers used in our experiment was implemented by using a multi-stratified training-testing selection to avoid selection and prediction biases. The creation of training and testing dataset was stratified both across participants ($N_s = 35$), targets ($N_i = 10$), and total number of trials ($N_t = 350$). The entire algorithm was repeated 100 times to control for suboptimal sampling. Metrics of performance accuracy and F-scores (which incorporates measures of recall and precision) were extracted to assess the validity of classifiers. Different classifiers were statistically compared by conducting the mid-p-value McNemar test of accuracies (Fagerlan et al., 2013).

RESULTS

Intrinsic brain-behavior Relationships

Starting from the hypothesis that intrinsic connectional profiles can support intrinsic affective-cognitive orientation, we investigated relationships between orientation scores and brain architectures. This was done by studying participation coefficients (i.e., cross-module communication) and within-module degree (i.e., intra-modular connections).

We found that resting-state participation coefficients were positively associated with orientation in a network encompassing prefrontal, cingulate, inferior parietal, and posterior temporal nodes (Figure 2A; $\beta = .014 \pm .006$, standardized $\beta = .104$, $t = 2.54$, $p = .01$). We label this as a frontoparietal (FP) network, since the brain regions involved (Figure 2B) overlap to the frontoparietal network discussed in literature (Di Plinio & Ebisch, 2018). A relevant degree of variability was observed within the FP network: nodes in the dorsomedial prefrontal cortex, dorsal-anterior cingulate cortex, and generally in the right hemisphere exhibited significantly above-average effects, while many nodes in the left hemisphere exhibited lower effects (test on random slopes; $p < .05$, FDR corrected). Such results were significant with medium-high structural resolutions ($\gamma > 2.5$, Figure 2C). No significant results were observed with respect to the within-module degrees.

The association between participation coefficients and orientation was investigated also using original scores: NFA and NFC. Resting-state participation coefficients of the FP network were not associated with NFA (Figure 2D; $\beta = .003 \pm .007$, 95% CI [-.010 .016], standardized $\beta = .020$, $t = 0.42$, $p = .67$). By contrast, a significant negative association was found between FP's participation and NFC (Figure 2E; $\beta = -.013 \pm .006$, 95% CI [-.025 -.001], standardized $\beta = -.091$, $t = -2.17$, $p = .029$). This pattern of results indicates that the compound score orientation is negatively associated with cross-network communication in a FP network, and this result is mainly driven by the negative association between participation and NFC. By comparing the standardized effect sizes, it can by observed that the negative effect of NFC on participation (-0.091) is more than four times bigger than the positive effect of NFA (.020).

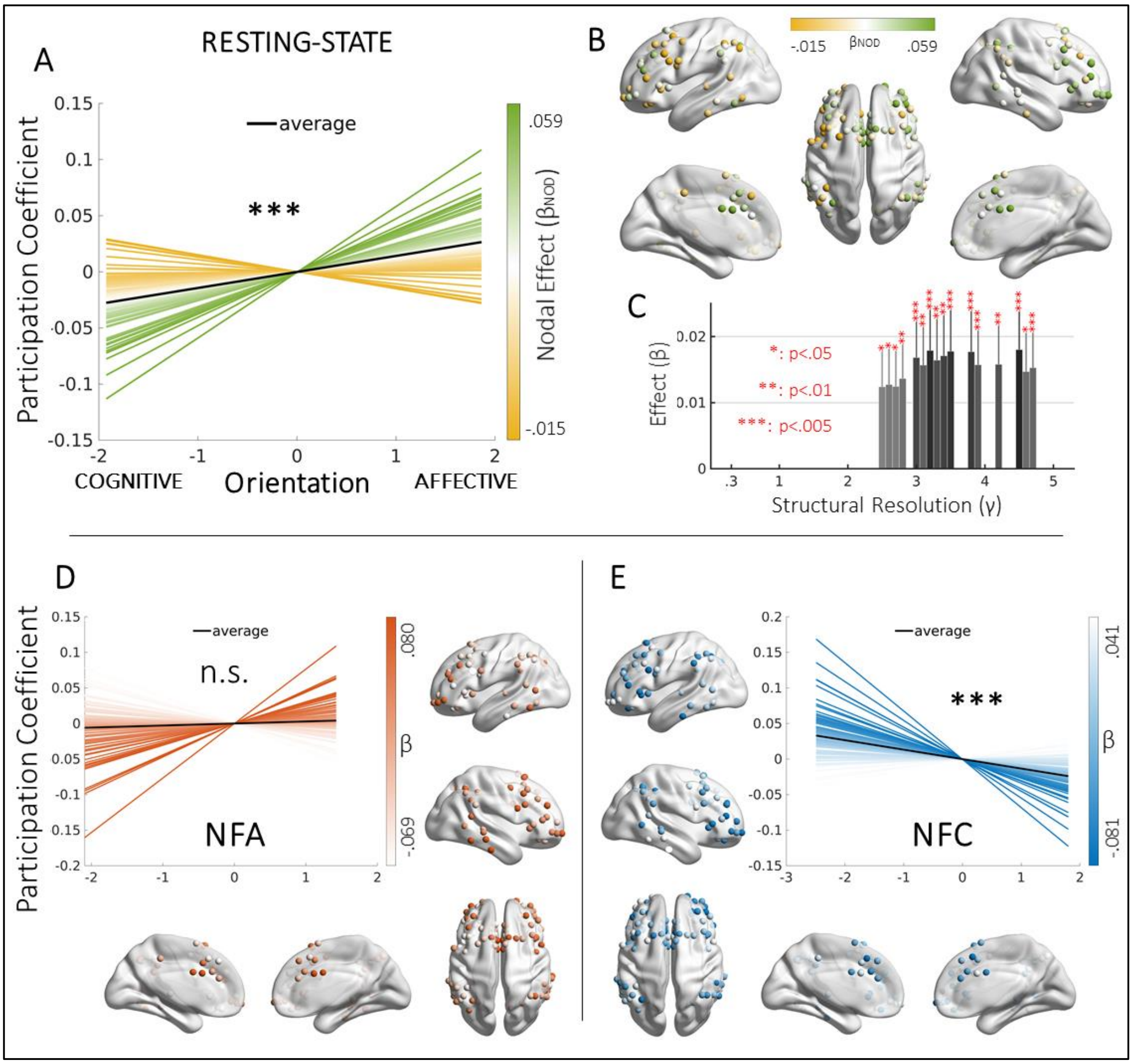

Figure 2. Resting-state results. The cross-network functional connectivity of the frontoparietal network (FP) was significantly associated with individual affective-to-cognitive orientation. (A) orientation versus participation coefficient in the FP module is plotted using model predictions (BLUPs). Each line represents predictions for a single node. The color-coding shows a more substantial effect in the left hemisphere (especially in mid-cingulate and orbitofrontal regions) and a weaker effect in the right hemisphere. (B) Structural configuration and nodal effect sizes for the FP module involved in the association. (C) Cross-gamma results indicate that the association between participation coefficient and orientation in the FP is true with medium and high structural resolutions ($\gamma > 2.5$). The subfigures (D) and (E) report the results of the same analyses for NFA and NFC, respectively. The association between NFA and participation in the FP module was not significant, although some distinct nodes in the orbitofrontal cortex and dorsal anterior cingulate showed positive effects. Instead, the association between NFC and participation in the same module was significant and especially strong in the right prefrontal cortex and bilateral anterior insula.

Prediction of individual choices through Machine-Learning

We used a semi-automated machine learning approach to evaluate and cross-validate the prediction performance for every possible combination of features (including intrinsic orientation, intrinsic connectivity, extrinsic brain activity, extrinsic evaluation). The highest prediction of individual behavioral choices was found in the classification model that combined intrinsic brain (connectional participation coefficients), intrinsic behavioral (orientation), and extrinsic behavioral (Evaluation) data. However, intrinsic brain-behavioral features alone were sufficient to yield a significantly high score in the prediction of choices.

In more detail, we found that combining intrinsic connectivity and behavioral orientation yielded a high classification performance (using separated NFA/NFC: accuracy = 0.70 ± 0.02; using the difference score orientation: accuracy = 0.69 ± 0.02). Moreover, the prediction using only extrinsic behavioral evaluations was high (accuracy = 0.76 ± 0.01). This result was not surprising, since the explicit behavioral ratings given by the participants during the fMRI scan are plausibly expected to correlate with the post-MRI behavioral choice of the product. Nevertheless, including both intrinsic and extrinsic elements significantly improved choice prediction (using separated affective and cognitive scores for orientation and evaluation: accuracy = 0.77 ± 0.02; using affective-cognitive difference scores for orientation and evaluation: accuracy = 0.78 ± 0.01), showing that extrinsic and intrinsic variables are encoding only partially overlapping information (Figure 3). The performances and the F-scores of these classifiers are reported in Figure 3A and 3B, respectively. The direct comparison of classifiers is shown by asterisks in the Figures. The comparison confirmed that the classification achieved by combining intrinsic brain-behavioral features and extrinsic evaluation outperformed other variable combinations. Contrary to our expectations, the extrinsic brain features (i.e., single-trial task-evoked activity) were not useful in predicting individual behavioral choices between affectively- and cognitively-presented items.

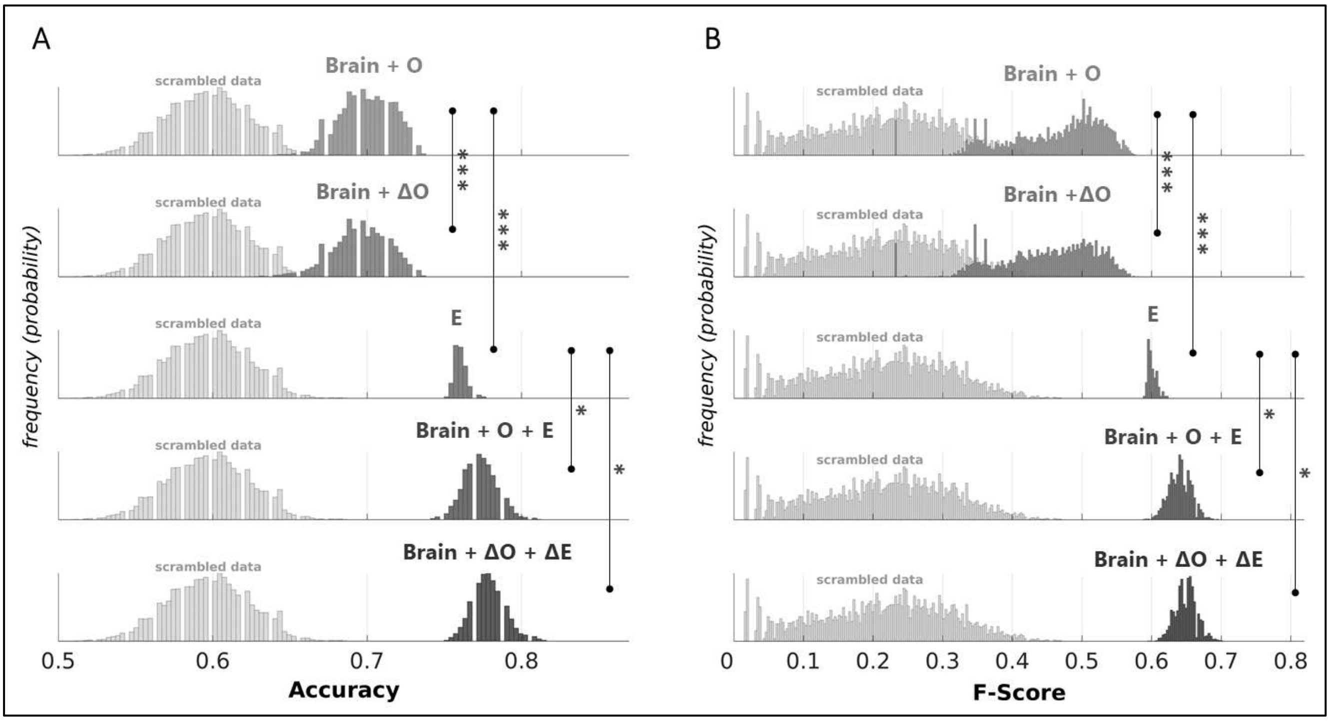

Figure 3. Model accuracies from machine learning. The subfigures (A) and (B) report the models' accuracy and F-score, respectively. Each subplot also reports a null classification model, which includes scrambled data. The best classifiers resulting from the semi-automated selection using SVM included intrinsic brain connectivity (Brain), intrinsic orientation (O=NFA & NFC, ΔO=orientation difference score), and extrinsic Evaluation (E=Affective evaluation & Cognitive evaluation, ΔE=evaluation difference score). In other words, when the classifier included these three variables, it had the best classification accuracy and F-score. Importantly, intrinsic features (Brain, O, ΔO) significantly increased the accuracy of the classifier when compared to the model with extrinsic evaluation alone. Note that the models E and ΔE have identical results. McNemar's mid p-value for model comparisons: *** = p < .001; * = p < .05. Results for the ordinal classification are reported in the supplementary materials.

Further, we investigated in more detail the classifier performances with respect to all the dimensions included in the analysis, that is, intrinsic behavior, extrinsic behavior, brain nodes, structural resolutions, items, and individuals. Analyzing behavioral contributions to the classifier, we found that the best intrinsic behavioral predictors of choice was the need-for-cognition score (predictor score for NFA = .0001; predictor score for NFC = .0071). **Conversely**, **participants' self-reported liking for the objects in the affective messages better predicted which object they ultimately chose** (predictor score for Affective Evaluation = .069; predictor score for Cognitive Evaluation = .002). As reported in Figure 4A, a higher participation coefficient of regions of the default mode network (in black, including medial prefrontal cortex, posterior cingulate, middle temporal gyrus) favors affective choices, whereas higher participation coefficients in secondary visual regions and task-positive regions (in white, including supramarginal gyrus and dorsolateral prefrontal cortex) favor cognitive choices.

It is worth noting that the results were rather stable across items (Figure 4B) and were unaffected by structural resolutions (Figure 4C). A moderate variability was observed in the prediction accuracy across participants (Figure 4D). These results show that, even if intrinsic features (i.e., brain & behavior) can predict the individual choice, the inclusion of information on the subjective Evaluation of items introduced by persuasive message content elicits a significantly stronger prediction accuracy.

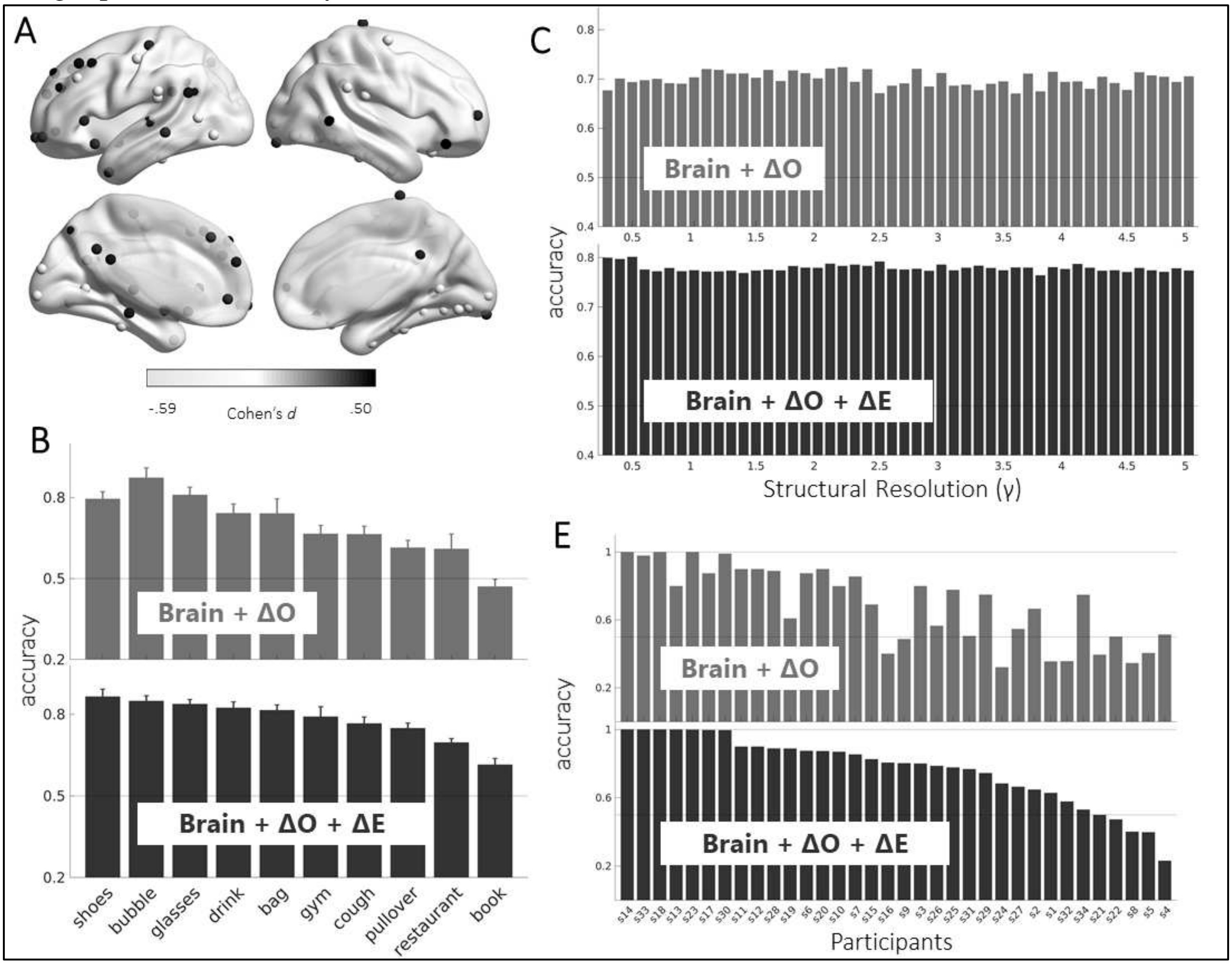

Figure 4. (A) Brain features included by feature selection encompassed default mode network regions, secondary visual areas, and task-positive temporal and parietal areas. As shown by the color-coding in the subfigure, higher participation coefficients for regions in the default mode network favor affective choices (black nodes), while higher participation coefficients in task-positive regions likely favor cognitive choices (white nodes). (B) Classification accuracy across items was relatively stable. (D) Classification accuracy did not change for increasing values of structural resolution used to define brain architectures. (D) Classification accuracy across participants showed a moderate variability. Results in B, C, and D refer to the models which included compound variables in Figure 3 (Brain + ΔO, Brain + ΔO + ΔE).

DISCUSSION

The present work uncovers the brain's functional architecture supporting individual's relative choices in the context of affective-cognitive persuasion. Using data collected via a comprehensive fMRI paradigm including resting-state and task-controlled states, we illustrate a multidimensional basis of persuasion incorporating intrinsic brain features (connectional brain profiles), extrinsic brain features (task-evoked activity), intrinsic behavior (affective and cognitive orientation), and extrinsic behavior (evaluation of items introduced by affective and cognitive messages). Firstly, our findings show that resting-state functional connectivity of fronto-parietal regions with high cross-network communication is associated with individual orientation, primarily via the need for cognition. Secondly, we highlight how intrinsic brain connectivity and orientation can efficiently predict if individuals will choose an item presented by an affective or cognitive persuasive message.

To our knowledge, our study is the first to show that cross-network connections of a large-scale frontoparietal (FP) module during the resting-state, as indexed by participation coefficients (that is, the strength of connections of a node other networks), predicted individual affective versus cognitive orientation. These brain nodes overlap with the FP network found in the literature (Di Plinio & Ebisch, 2018). Affectively oriented individuals showed a prevalence of cross-network participation from FP nodes in the right hemisphere, especially in the mid-cingulate and orbitofrontal regions. By contrast, cognitively oriented individuals showed stronger cross-network connections from FP nodes in the left hemisphere. **To note, the labels "affectively oriented" or "cognitively oriented" reflect a relative difference between NFA and NFC scores among sample participants.** Nodes of the FP network participate in disparate processes including mirror mechanisms (Molenberghs et al., 2012), higher-order functions such as adaptive task-control (Dosenbach et al., 2008; Zanto & Gazzaley, 2013), executive working memory (Nee et al., 2013; Wallis et al., 2015), and decision-making during goal-oriented behavior (Menon, 2011). Considering our findings, the connectional profile of the FP network likely contributes to establishing a personal "baseline" inclination towards decisional processes in affective or cognitive contexts. Our findings confirm that hemispheric asymmetries epitomize the diversification of subjective orientations within the population since stronger intrinsic extra-network connections from right FP nodes favor a predominantly affective orientation.

Implementing cross-validated machine-learning techniques, we found that intrinsic brain connectional profiles and intrinsic orientations can efficiently predict individual choices between targets introduced by affective versus persuasive cognitive messages. As expected, the prediction using extrinsic behavioral evaluations was also high, confirming that attitude is an important predictor for behavioral choices (Fishbein & Ajzen, 1975; Maio et al., 2018). However, including both intrinsic and extrinsic elements allowed a better choice prediction, showing that extrinsic and intrinsic variables are encoding only partially overlapping information. Contrary to our expectations, the extrinsic brain feature (i.e., single-trial task-evoked activity) did not predict choice. Analyzing behavioral contributions to the classifier, we found that the best behavioral predictors of choice were individual need for cognition scores and individual evaluation of the targets introduced by affective messages. Analyzing the brain contributions to the classifier, we found that the weight of cross-network connections from different brain subnetworks (default-mode vs sensory and "task-positive" regions) incline the individual toward specific behavioral choices (choice of affective vs cognitive targets, respectively). From these findings, we can understand that the intrinsic individual brain-behavior architecture plays a key role in task-driven choices following persuasive messages.

Future studies may bring further insights into persuasive matching by analyzing and directly contrasting the persuasion power of affective matching (i.e., delivering affective messages to affectively oriented individuals) and cognitive matching (i.e., delivering cognitive messages to cognitively oriented individuals). Note that this would be possible with an ad-hoc experimental design to measure differential persuasion outcomes. Future studies may also consider bridging the cognitive neuroscience framework presented here with other social aspects like engagement and passion, which enhance behavioral and neural responses (Shane et al., 2020; Massaro et al., 2020) with possible repercussions on persuasion.

Our study is exposed to some limitations. First, the behavioral variables measured in the persuasion task may depend on the subjective efficiency of information processing (e.g., different levels of message processing). This effect may, in turn, affect the observed variables. However, we implemented a controlled experiment in which the selection of physical and psychological features of affective and cognitive messages were strictly controlled (see Methods) and stimuli were tested on two pilot studies (96 total additional subjects) for their understandability. **In other words, we accurately limited effects unrelated to the factors of interest following findings from previous research that showed how matched messaged are processed more deeply than unmatched messages (Petty & Wegener, 1998; Haddock et al., 2008).** Thus, sources of unwanted variance have been minimized so that such bias is likely to be very weak in our study. **Second, although we labelled an outcome variable as "choice", we would like to clearly express that, at an operational level, this variable measures the *relative preference* of the subject toward an affective *or* a cognitive item, rather than a direct choice per se. Third, trial-based activity estimation may entail a large amount of noise, which can eventually impact the analysis. Perhaps future**

paradigms may include parallel experimental conditions of persuasion/choice versus only perception of equivalent stimuli to characterize task-related phenomena.

To conclude, we implemented a comprehensive procedure and a controlled, cross-validated model testing, which endorse high confidence about our findings on the neural basis of persuasion. Environmental factors (Mayer & Tormala, 2010; Falk & Scholtz, 2018), cultural and personal background (Liang et al., 2014; Haddock & Huskinson, 2004; Slater & Rouner, 2006), and the type of goal-directed behavior requested (Nee et al., 2013; Cooper et al., 2017; Cacioppo & Petty, 1982; Haddock & Maio, 2019) are just a few of the variables that may influence the weight of specific neural subsystems in decisional processes. Further studies could corroborate and complement the models proposed here. **For example, while affect has shown a stronger matching effect, we found need for cognition (NFC) but not need for affect (NFA) to be related with cross-network communication. It is possible that the persuasion processes following a "highly affective profile" (high NFA) observes other neuro-functional principles which are at least partially independent from the inter-network communication studied here.**

Nevertheless, our investigation unveils meaningful relations between intrinsic and extrinsic dimensions in the study of the neurocognitive signatures of persuasion. Since individual orientation is relatively stable over time (Haddock et al., 2008), our findings likely hold across diversified contexts. Our findings may also have implications for theories and designs of persuasive messaging interventions, suggesting that individual decisions depend on the interaction between individual orientation and how the brain circuitry is shaped from past experiences. This dependency may help explain and provide future insight into studying the interindividual variability in the effectiveness of strategies to promote positive lifestyles (Walter et al., 2019). Concerning the emotion/reason dichotomy noted at the start of the paper, we suggest that individuals effectively bear intrinsic neural and behavioral predispositions toward affective (emotional) or cognitive choices (reason). However, the personal neurocognitive background may drive decisional processes based on the subjective value given to specific targets.

Data Availability Statement

Data and code used for this study will be available upon request to the corresponding author after publication.

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