

Neural representations in mPFC and insula encode individual differences in estimating others' preferences

Hyeran Kang^{1,2,†}, Kun Il Kim^{2,†}, Jinhee Kim², Hackjin Kim^{2,*}

¹Department of Psychology, University of Michigan, Ann Arbor, MI 48109, USA

²Laboratory of Social and Decision Neuroscience, School of Psychology, Korea University, Seoul, 02841, Republic of Korea

*Corresponding author. Hackjin Kim, Ph.D., School of Psychology, Korea University, 145 Anam-ro, Seongbuk-gu, Seoul, 02841, Republic of Korea.

E-mail hackjinkim@korea.ac.kr

[†]These authors contributed equally.

Abstract

In human society, successful social interactions often hinge upon the ability to accurately estimate other's perspectives, a skill that necessitates integrating contextual cues. This study investigates the neural mechanism involved in this capacity through a preference estimation task. In this task, participants were presented with the target's face and asked to predict their preference for a given item. Preference estimation accuracy was assessed by calculating the percentage of correct guesses, where participants' responses matched the target's preferences on a 4-point Likert scale. Our research demonstrates that, based on inter-subject representational similarity analysis (IS-RSA), the multi-voxel patterns in the medial prefrontal cortex (mPFC) and the anterior insula (AI) predict individual differences in preference estimation accuracy. Specifically, the varying behavioural tendencies among participants in inferring others' preferences were mirrored in the multivariate neural representations within these regions, both of which are known for their involvement in individual differences in interoception and context-dependent interpretation of ambiguous facial emotion. These findings suggest that mPFC and AI play pivotal roles in accurately estimating others' preferences based on minimal information and provide insights that transcend the limitations of traditional univariate approaches by employing multivariate pattern analysis.

Keywords: inter-subject representational similarity analysis; anterior cingulate cortex; theory of mind; interoception; face

Introduction

In daily life, people often form impressions of others and make judgments based on highly limited information, which is referred to as 'thin-slicing' in psychology (Ambady and Rosenthal 1992). Such an ability demonstrates how people use fast and automatic processes to make decisions, such as interpreting nonverbal cues like facial expressions, gestures, and tone of voice during interactions. For example, reading a text about a person's major life events can predict their personality (Pennebaker and King 1999), and simply observing someone's room can accurately judge their personality (Gosling et al. 2002). Moral judgments can be made from brief visual scenes (De Freitas and Hafri 2024), and after watching a 60-second video of a social interaction, one can predict the other person's socioeconomic status (Kraus and Keltner 2009).

Among others, facial cues are particularly integral to social inference, serving as a rich source of insight into an individual's traits (Zebrowitz et al. 2002, Frith and Frith 2012). Previous studies have shown that, in less than 100ms, one can infer how trustworthy someone is (Willis and Todorov 2006), predict a company's financial performance by looking at the CEO's face (Rule and Ambady 2008b), accurately assess someone's sexual orientation (Rule and Ambady 2008a), and predict the outcomes of political candidates in elections (Todorov et al. 2005).

Numerous psychological literatures highlight the significance of intuitive social inferences, in which individuals are tasked with inferring affective states or psychological traits of targets. These

tasks encompass estimating transient emotional states as interpreted through facial expressions (Frith and Frith 2012), understanding intentions of approach and avoidance (Jones and Kramer 2021), and discerning psychological traits such as trustworthiness (Van't Wout and Sanfey 2008, Chwe and Freeman 2023), cooperativeness (Tognetti et al. 2013), intelligence (Zebrowitz et al. 2002), and preferences (North et al. 2010, 2012, Kang et al. 2013, Eggleston et al. 2015, Pollmann and Scheibehenne 2015, Vijayakumar et al. 2021). These intuitive social inferences, based on facial information, are integral components of understanding others, including empathy and the theory of mind (Quesque and Rossetti 2020), yet the exact neural mechanisms behind these instinctual inferences require further exploration.

What factors determine the accuracy of predicting others' traits based on limited information, such as a face? Research conducted to answer this question so far suggests that higher emotional recognition ability (Jaksic and Schlegel 2020) and intuitive over analytical thinking (Albrechtsen et al. 2009) are associated with higher accuracy in thin-slicing. Compared to the vast psychological research on thin-slicing, studies on the neurological mechanisms related to this phenomenon are relatively scarce, especially regarding the biological factors that differentiate individuals with high and low accuracy in thin-slicing. Research that identifies the neurological characteristics underlying individual differences in thin-slicing accuracy is expected to provide important insights into distinguishing innate from acquired factors in this phenomenon.

Our laboratory has previously reported on the significant role of the dorsomedial prefrontal cortex (dmPFC) communicating with

the temporoparietal junction (TPJ) in predicting others' preferences based on facial features and the associated individual differences in accuracy (Kang et al. 2013, Park et al. 2018). Prior research in social cognition suggests that the dmPFC, in concert with the TPJ, forms the core of the mentalizing network (Schnell et al. 2011, Dvash and Shamay-Tsoory 2014). Meta-analyses indicate that dmPFC activities are engaged when observing others receiving painful stimuli (Lamm et al. 2011), estimating others' thoughts through perspective-taking, and inferring their emotional states (Schurz et al. 2014, 2021), emphasizing its role in abstract representation based on external information for generating appropriate affective and cognitive behaviours (Kim 2020). Beyond mentalizing studies, the dmPFC is involved in generating new actions based on prediction errors and learning abstract rules (Seo et al. 2014) and representing other-regarding values for prosocial decisions (Sul et al. 2015). Increased dmPFC activity during the observation of social scenarios correlates with a higher frequency of social interactions (Powers et al. 2016). Similarly, dmPFC activities are instrumental in predicting others' behaviour (Amodio and Frith 2006) and showed a positive correlation with the accuracy of preference estimation based on facial appearance (Kang et al. 2013).

Multivariate pattern analysis (MVPA) is a statistical technique used to analyse brain imaging data. Unlike traditional univariate analysis, which examines activity of one voxel at a time, MVPA analyzes patterns of activity across multiple voxels simultaneously, making it more sensitive to detecting subtle differences between psychological states (Norman et al. 2006). Supporting evidence shows that multivariate analyses reveal unique activity patterns in brain regions that are commonly activated across conditions in univariate analyses (Woo et al. 2014, Krishnan et al. 2016, Wake and Izuma 2017, Kim and Kim 2021). Considering the differences between these two methods, it is necessary to determine whether the role of the dmPFC, linked to individual differences in the accuracy of predicting others' preferences, remains valid in both univariate and multivariate analyses, or if there are specific differences between the two methods related to these individual differences.

In this study, we delve into the neural mechanisms underlying individual variations in preference estimation accuracy. First, we aimed to replicate the findings regarding the role of the dmPFC in accurately evaluating other's preferences, as previously reported by Kang et al. (2013). Secondly, we opted to capitalize on recent advances in MVPA techniques, renowned for their capability to map hidden neural representations of psychological traits and motivations that could not be captured by conventional univariate approaches (Kragel et al. 2021, Contreras-Huerta et al. 2023). To achieve this, we employed a preference estimation task, where participants were shown an image of a person followed by an image of a food or movie poster (Kang et al. 2013) and asked to infer the preference of the person to the image solely based on their facial appearances. Our study leveraged inter-subject representational similarity analysis (van Baar et al. 2019) to identify the specific brain regions where activity patterns are correlated with individual variability in the accuracy of preference estimation.

Materials and methods

Participants

A total of 39 healthy female participants, aged between 22 and 44 (all females; mean age = 30.82), were recruited for this study. The decision to recruit only female participants was based on prior research (Carney et al. 2007), which suggests that female participants tend to make more accurate thin-slice judgments compared to male participants. By selecting a single gender cohort, we sought

to minimize potential gender effects. All participants were right-handed, had no visual impairments, and reported no history of psychiatric or neurological conditions. However, due to artefacts in neuroimaging data, one participant's data was excluded. Thus, final analyses were conducted on 38 participants (age range: 22–44, mean age = 30.56). To determine whether our study had sufficient statistical power, we conducted a Bayesian power analysis. Unlike traditional frequentist power analysis, which assumes a fixed effect size, Bayesian approaches incorporate empirical uncertainty to provide a more robust and realistic assessment of power (Du and Wang 2016, Kruschke and Liddell 2018). Based on our observed effect size ($r = .566$) and a final sample size ($N = 38$), the probability that the true effect size exceeds $r = .34$ is 95.27%. This threshold of $r = .34$ was derived from a transformation of the effect size reported in Kang et al. (2013). These results suggest that our study was well-powered to detect meaningful effects within the expected range, thereby confirming the robustness of the hypothesized relationship. All participants provided informed consent, in accordance with the guidelines set by the Institutional Review Board of Korea University. These participants performed a facial expression recognition task prior to this task, and these data have already been published elsewhere (Kim et al. 2022).

Procedure

Upon arrival, participants' eligibility for MRI scanning was verified. Before scanning, participants were given instructions and completed a couple of practice trials to familiarize themselves with the experimental paradigm. The primary task was the preference estimation paradigm adapted from Kang et al. (2013), designed to investigate neural mechanisms associated with inferring preferences (e.g., for movie posters or food items) based on facial photographs of targets. The photos of targets were collected from an independent group of eight individuals (four males, four females; all Korean) who had provided their preferences for five distinct food items and five distinct movie stimuli.

Following the methodology established by Kang et al., we selected food and movie posters as stimuli to best allow participants to estimate others' preferences accurately. In their study, various item categories were evaluated, including movies, books, bags, shoes, and foods, to determine which categories would best facilitate accurate preference estimation. Items were selected based on preference ratings, focusing on those with intermediate levels of preference and high variability, to minimize overlap between general population preferences and individual target preferences. Their findings indicated that participants could reliably estimate preferences for movies and foods, while accuracy was lower for other categories such as books and bags. This suggests that, in certain domains, participants were able to accurately estimate others' preferences, even with very brief exposure to limited information, such as facial appearance. Given these considerations, we adopted food and movie posters as stimuli in our study, aligning with prior research demonstrating that these categories are suitable for assessing accuracy in estimating others' preferences.

To enhance participants' engagement in estimating the targets' preferences, they were informed that monetary incentives would be given based on their relative performance. Notably, no participant had prior familiarity with any of the photo targets. Before the MRI scanning, participants also provided facial photographs for later use in their own personal preference estimation condition.

During the single MRI session, which lasted approximately 18min, participants performed the preference estimation task (Fig. 1), with trials presented in event-related paradigms. Each trial began with a 3-second display of a facial photo (either of the

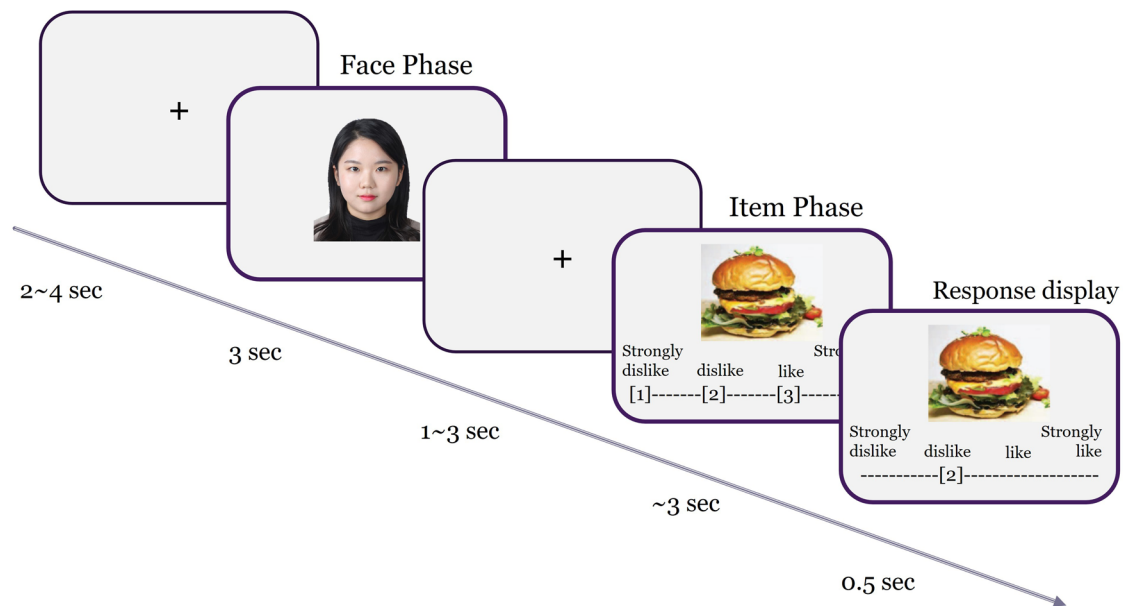


Figure 1. Task design. In the preference estimation task, the participants were asked to infer the target's preference for a given item. A target was presented during the face phase for 3 s in the target-trials, and then an item was displayed. During the item phase, the participants had to perceive an item and rate how much the target would favour this specific item on a 4-point scale. When the participants answered, their response was shown on the screen for 0.5 s.

participant self or a target), followed by a jittered fixation interval lasting 2–4 seconds. Subsequently, an item was displayed, and participants provided their own preference (self-trial) or guessed the targets' preference (target-trial) for the depicted item using a 4-point Likert scale (from 'strongly dislike' to 'strongly like') within a 3-second response window. Immediately after the response, participant's choice was displayed on the screen for 0.5 seconds. It is important to note that the 'participant's choice' here refers to the predictions and preference inferences made solely by the participants, rather than feedback on the actual preferences of the targets. No information about the actual preferences of the 8 targets was provided to the participants at any point in the study. Therefore, there was no chance for participants to learn or adjust their predictions based on feedback. Each prediction was made independently on each trial, based solely on the participants' judgement without any external information influencing subsequent estimations. The MRI session comprised 10 self-trials and 80 target-trials (i.e., facial photo (9) \times item (10)). Trials were presented in a pseudo-random order. In the post-scan session, participants were debriefed about the study's objectives and compensated with 40,000 KRW (approximately \$38).

Behavioural data analysis

We measured preference estimation accuracy by assessing the proportion of trials where participants' estimations precisely matched the targets' stated preferences. Only exact matches were considered correct when calculating the accuracy score. For instance, if a target rated an item as 3 (like) and a participant estimated it as 2 (dislike), it was marked incorrect. Similarly, if a target rated an item as 3 (like) and the estimation was 4 (highly like), despite both being positive, the trial was still deemed incorrect. Overall, the accuracy of participants' estimation was significantly above the chance level (0.25) on average (Fig. 2), meaning that participants can infer others' preference from their faces better than random guessing ($M = 0.31$, $t_{(37)} = 5.91$, $P < .001$). Furthermore, we conducted supplementary analyses covering various aspects, including baseline preferences for movie and food stimuli (Supplementary Fig. S1), preferences by target gender

(Supplementary Fig. S2), participants' accuracy rates for each target (Supplementary Fig. S3), accuracy differences between movie and food stimuli (Supplementary Fig. S4), and performance comparisons between high and low accuracy groups (Supplementary Fig. S5).

fMRI data acquisition

All the neuroimaging data were collected from a 3T Siemens Trio MRI scanner (MAGNETOM Trio, A Tim System; Siemens AG, Erlangen, Germany) with a 12-channel head coil located at the Korea University Brain Imaging Center. We acquired functional images using gradient echo-planar images (EPI) with Blood Oxygenation Level-Dependent contrast (TR = 2000ms; TE = 30ms; flip angle = 90°; FOV = 240mm; $3 \times 3 \times 3$ mm in-plane resolution; 80×80 matrix size; and 36 slices with no gap with interleaved sequence), and high-resolution structural images (TR = 1900ms; TE = 2.52ms; flip angle = 9°; $1 \times 1 \times 1$ mm in-plane resolution; and 256×256 matrix size). The experiment task was presented through an MR-compatible LCD monitor mounted on a head coil (refresh rate: 60Hz; display resolution: 640×480 pixels; viewing angle: 30°) operating on MATLAB 2009b with Cogent 2000 stimulus presentation software.

Image preprocessing

The functional data were preprocessed by using the default preprocessing pipelines of the CONN toolbox 2018b (www.nitrc.org/projects/conn, RRID: SCR_009550; Whitfield-Gabrieli and Nieto-Castanon 2012). The images were first realigned and unwarped, centred to (0, 0, 0) coordinates, and slice-time corrected in sequential order. The resulting images were then spatially normalized to the standard Montreal Neurological Institute 152 reference template resampled to 2mm isotropic voxels. Finally, the normalized images were then smoothed with an 8-mm full-width at half-maximum Gaussian kernel.

Neuroimaging data analysis: Univariate approach

In the first-level analyses, we processed the neuroimaging data utilizing SPM12 software (Wellcome Department of Imaging

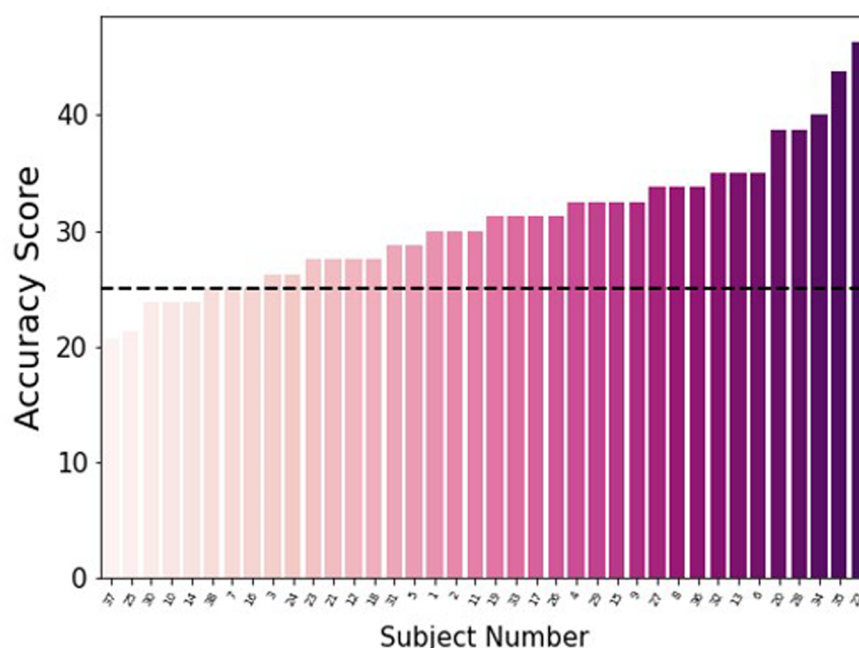


Figure 2. Accuracy scores (percentage) of each participant. Participants scored above the chance level (dot line) on average ($M = 0.31$, $t_{(37)} = 5.91$, $P < .001$).

Neuroscience, London, United Kingdom). Individual participant data were modelled using a general linear model (GLM), which incorporated five regressors: (i) the self-trial during the face phase, (ii) the target-trial during the face phase, (iii) the self-trial during the item phase, (iv) the target-trial during the item phase, and (v) button response onset. Additionally, we accounted for head-motion artefacts by including six head-motion regressors as covariates of no interest.

To identify brain regions associated with individual preference estimation performance, we performed a linear regression analysis, incorporating the contrast images derived from target-trials versus self-trials during the item phase and individual accuracy scores as covariates. A parallel analysis was applied to the data obtained during the face phase.

To precisely examine our primary hypothesis—that there exists a correlation between the activation of the dmPFC and the participants' accuracy scores, as suggested by previous research utilizing the same paradigm (Kang et al. 2013)—we utilized a dmPFC binary mask. This mask was derived from a meta-analysis by de la Vega et al. (2016), which segmented the medial prefrontal cortex (mPFC) into nine distinct subregions based on each region's functional coactivation maps. Our methodological choice was guided by our focused research question, leading us to opt for a univariate approach exclusively targeting the dmPFC subregion [A1], excluding other mPFC subregions from our analysis. This approach was not only aimed at confirming previous findings but also at providing a rigorous test of the role this particular subregion plays in the task at hand, thereby advancing our understanding of the functional specialization within the mPFC in the context of preference estimation. In addition to our primary objective, we sought to determine if other subregions of the mPFC played a role in the preference inference process. To this end, we conducted further analysis using an mPFC binary mask that encompasses dmPFC [A1], pgACC [A2], and vmPFC [A3].

The motivation to accurately infer others' preferences can conflict with the motivation to express one's own preferences. According to our model, such conflicts between motivation embedded in the vmPFC appear to be resolved through close communication

with the dmPFC, leading to value adjustment (Kim 2020). Based on this hypothesis, in addition to the GLM-based fMRI data analysis, we ran a generalized psychophysiological interaction (gPPI) analysis (McLaren et al. 2012), which is particularly useful in examining task-dependent functional connectivity, to test if individuals with high accuracy in predicting others' preferences would exhibit stronger functional connectivity between the vmPFC and dmPFC in the 'other' condition compared to the 'self' conditions. At an individual level, a voxel of interest (VOI) was extracted with the 5mm sphere around the peak (coordinates: $x = 0$, $y = 38$, $z = -10$) of the vmPFC cluster found in the multiple regression analysis. We utilized this VOI as a seed region. Time series were extracted from the vmPFC and served as the physiological variable, reflecting the neural activity in that region during the task. The contrasts for target- versus self-trials during the item phase served as the psychological variable. Then, the physiological and psychological variables were multiplied to create the PPI term. Finally, the individual accuracy scores were regressed with the contrast images of PPI term.

Our particular interest was the functional coupling between the mPFC subregions, with a specific focus on the vmPFC and dmPFC. To implement this analysis, we used an dmPFC binary mask [A1], consistent with the GLM-based approach above. This allowed us to explore whether the contextual connectivity strength within the mPFC increased during target-trials compared to the self-trials among the participants with higher accuracy scores.

Neuroimaging data analysis: Multivariate approach

We utilized MVPA to identify brain regions that encapsulate inter-subject variability during the estimation of preferences based on facial feature processing. In our study, we employed inter-subject RSA (IS-RSA; van Baar et al. 2019) to identify regions associated with variability in preference estimation accuracy. The main question was which brain regions exhibited similar activation patterns among participants with comparable accuracy scores in estimating others' preferences.

First, we segmented the entire brain into functionally relevant regions using a predefined 200-parcel map from the Neurosynth

database (<https://neurosynth.org/>). This map organizes the global brain atlas based on meta-analytic functional coactivation patterns. In our analysis, 183 parcels were included, omitting seventeen parcels due to their absence in our scan scope. Given prior research indicating distinct statistical properties between univariate and multivariate approaches (Jimura and Poldrack 2012, Coutanche 2013, Davis et al. 2014), we extended the ROI map initially used for univariate analysis. Importantly, MVPA captures heightened sensitivity to within-subject voxel variability but displays diminished sensitivity to inter-subject mean activation variability compared to univariate analyses (Davis et al. 2014). To understand individual differences in preference accuracy, we computed a behavioural dissimilarity matrix by calculating the absolute difference in accuracy scores among all participant dyads.

Subsequently, we constructed an inter-subject dissimilarity matrix for each of the 183 neural activation map parcels to assess inter-subject dissimilarity in mean activity patterns during the inference of the target's preference. We used the identical contrast map as in the univariate analyses for inter-subject representational similarity analysis (IS-RSA). Of particular interest were the target-trials compared to self-trials during the item and face phases. To identify brain regions where neural representations corresponded with behavioural inclination, we computed a nonparametric Kendall's tau-a correlation between the parcel dissimilarity matrices and the behavioural ones (Nili et al. 2014). The significance of tau-a

was validated through permutation testing. Specifically, while retaining the neural Representational Dissimilarity Matrix (RDM), we randomized the behavioural RDM 10,000 times to create a null distribution. To account for multiple comparisons, we adjusted the P-values using an FDR correction, and P-values below .01 post-adjustment indicated a significant correlation between inter-subject behavioural patterns of preference estimation accuracy and neural representation patterns of the parcel.

Results

Neuroimaging results: Multiple regression analysis with estimation accuracy as covariate

Our primary objective in the univariate analysis was to replicate the findings of the previous study (Kang et al. 2013), regarding the involvement of the dmPFC in accurately estimating another person's preferences with limited information. From the mPFC subregions (de la Vega et al. 2016), we included dmPFC area [A1] as binary mask for a regression analysis. Individual contrast maps of target- vs. self- trials were regressed against individual accuracy scores as a covariate. As predicted, during the item phase, we found a significant correlation in the dmPFC: a right cluster (peak coordinates: $x = 8, y = 46, z = 50$, small volume correction (SVC) corrected, $P_{SVC-peakFWE} = 0.028$) and a left cluster (peak coordinates: $x = -10, y = 44, z = 50$, small volume correction (SVC) corrected, $P_{SVC-peakFWE} =$

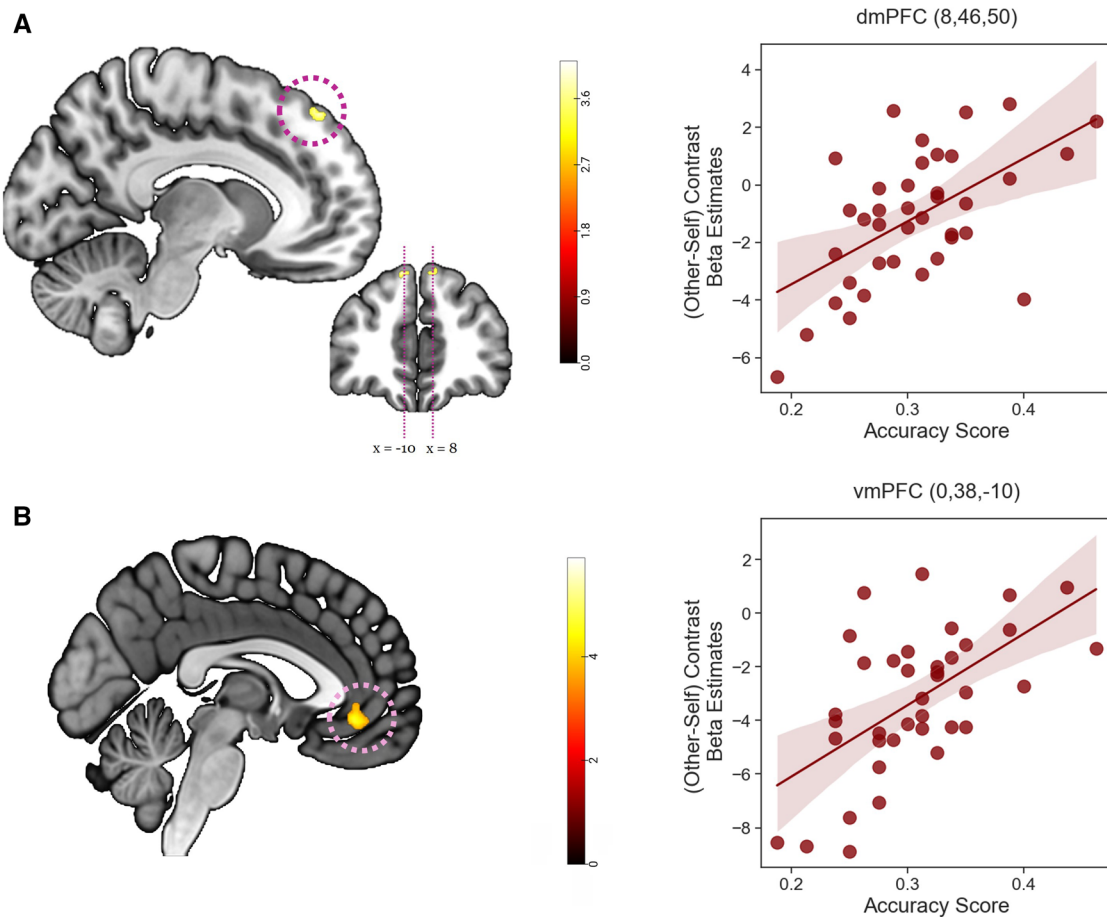


Figure 3. Univariate results. The mPFC activity predicts the estimation accuracy score. (A) The neural activations of the dmPFC (peak coordinates: $x = 8, y = 46, z = 50$) were positively correlated with how accurately participants guessed the targets' actual preferences (SVC corrected, $P_{SVC-peakFWE} = 0.028$) during the item phase. (B) The vmPFC (peak coordinates: $x = 0, y = 38, z = -10$) activity also positively correlated with the accuracy score (SVC corrected, $P_{SVC-clusterFWE} = 0.028$) during the item phase. The scatterplot of the mPFC activations and the accuracy score is presented on the right side. The shaded area indicates the 95% confidence interval.

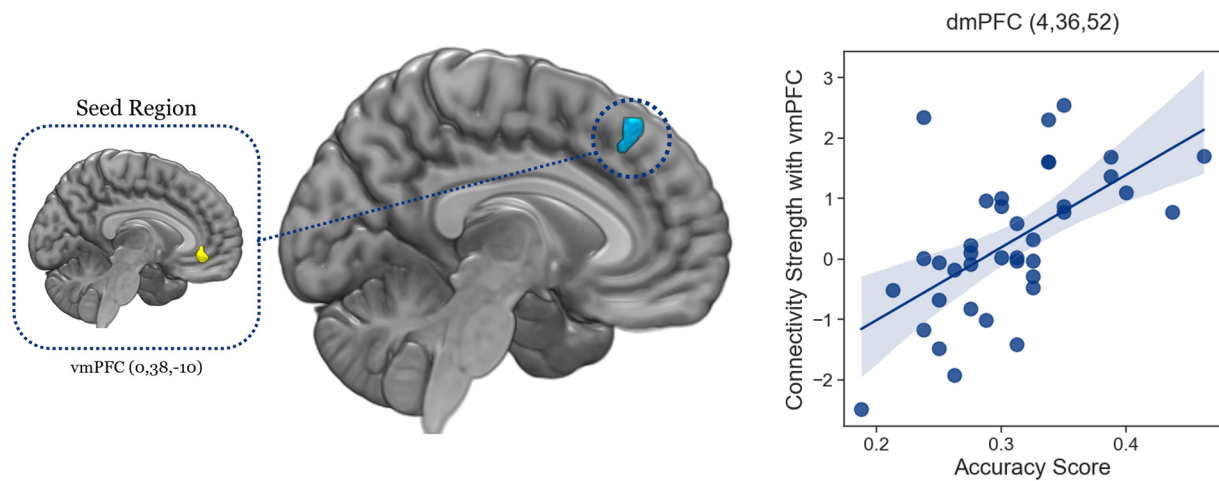


Figure 4. gPPI result. The functional connectivity of the vmPFC and dmPFC is linked to higher accuracy scores in estimating targets' preferences. A heightened psychophysiological interaction with vmPFC activity was observed in the dmPFC (peak coordinates: $x = 4$, $y = 36$, $z = 52$, small volume correction (SVC) corrected, $P_{\text{SVC-peakFWE}} = 0.034$) during target-trials compared to self-trials. The scatterplot on the right side illustrates the relationship between the strength of connectivity between the vmPFC and dmPFC and individual accuracy scores in estimating preferences, with the shaded area indicating the 95% confidence interval.

0.038) (Fig. 3). This suggests that individuals with higher accuracy scores exhibited greater activity within these clusters during the evaluation of items for the targets compared to themselves. No significant correlation was found during the face phase.

Although the dmPFC was the primary ROI of the regression analysis, we performed additional analysis to explore whether other regions of the mPFC was engaged in accurately inferring other's preferences. Therefore, we included other mPFC subregions, including dmPFC [A1], pgACC [A2], and vmPFC [A3], as a mask. The result revealed a significant correlation in the vmPFC (peak coordinates: $x = 0$, $y = 38$, $z = -10$, small volume correction (SVC) corrected, $P_{\text{SVC-clusterFWE}} = 0.028$) during the item phase. Conversely, no significant correlation was found during the face phase. In addition, no brain regions showed significant results after correction for multiple comparisons at the whole-brain level.

Neuroimaging results: Functional connectivity between vmPFC and dmPFC in relation to individual estimation accuracy score

Multiple regression analysis revealed that not only did dmPFC but also vmPFC regions activated more strongly as the participants' accuracy score increased. To examine the underlying rationale, we delved into the neural connectivity within mPFC subregions in relation to individual variations in preference estimation accuracy. This scrutiny pinpointed a significant cluster in the dmPFC (peak coordinates: $x = 4$, $y = 36$, $z = 52$, small volume correction (SVC) corrected, $P_{\text{SVC-peakFWE}} = 0.034$, Fig. 4). Specifically, functional connectivity between the vmPFC and dmPFC intensified among the participants with higher accuracy when discerning targets' preferences compared to when expressing their own preferences.

Neuroimaging results: Inter-subject representational similarity analysis (is-RSA)

Significant inter-subject representational similarity effects were found in four brain parcels, during the item phase, including the ventral anterior insula (vAI), the dorsal anterior insula (dAI), and the pregenual anterior cingulate cortex (pgACC) (Fig. 5). This implies that the inter-subject dissimilarity of neural activity patterns during the estimation of others' preferences corresponded to the inter-subject distance pattern of accuracy score. Conversely, no significant is-RSA

effect was yielded during the face phase. These results indicate that individuals with similar accuracy scores shared similar multi-voxel patterns only during the item phase, not when processing the facial features of the target.

Notably, the pgACC parcel identified through the is-RSA did not overlap with the vmPFC cluster obtained through the univariate approach (Fig. 6). Despite their close proximity, the absence of overlap suggests that both analytical methods can yield analogous yet distinctly separate outcomes. When using continuous measures, such as distance from the correct rating and its inverse, only the insula showed significant association with preference estimation in multivariate analysis, with no significant regions in univariate analysis. This suggests that exact accuracy may be closely linked to specific neural mechanisms, highlighting the role of precision in social inference tasks.

Discussion

This study investigated the neural underpinnings associated with individual differences in the ability to infer others' preferences based solely on facial cues. Consistent with the findings of Kang et al. (2013), considerable variability emerged among participants in their accuracy of estimating others' preferences, with some individuals demonstrating adeptness while others exhibit less precision. This behavioural variation corresponded with distinct patterns observed in the neuroimaging data collected during the task. Univariate analysis reaffirmed the role of the dmPFC in preference estimation, particularly highlighting its activity during the item phase as indicative of the accuracy in inferring others' preferences. Furthermore, multivariate analysis, particularly the results from IS-RSA, showed correlations between participants' estimation accuracy patterns and neural activity patterns in the pgACC, ventral AI, and dorsal AI during the item phase. Collectively, these findings underscore the central role of the mPFC and insula in the process of estimating others' preferences.

Understanding others' minds involves recognizing their thoughts and emotions, even when these mental states are not directly observable. Traditionally, two key concepts, Theory of Mind (ToM) and empathy, have framed these social cognitive capacities.

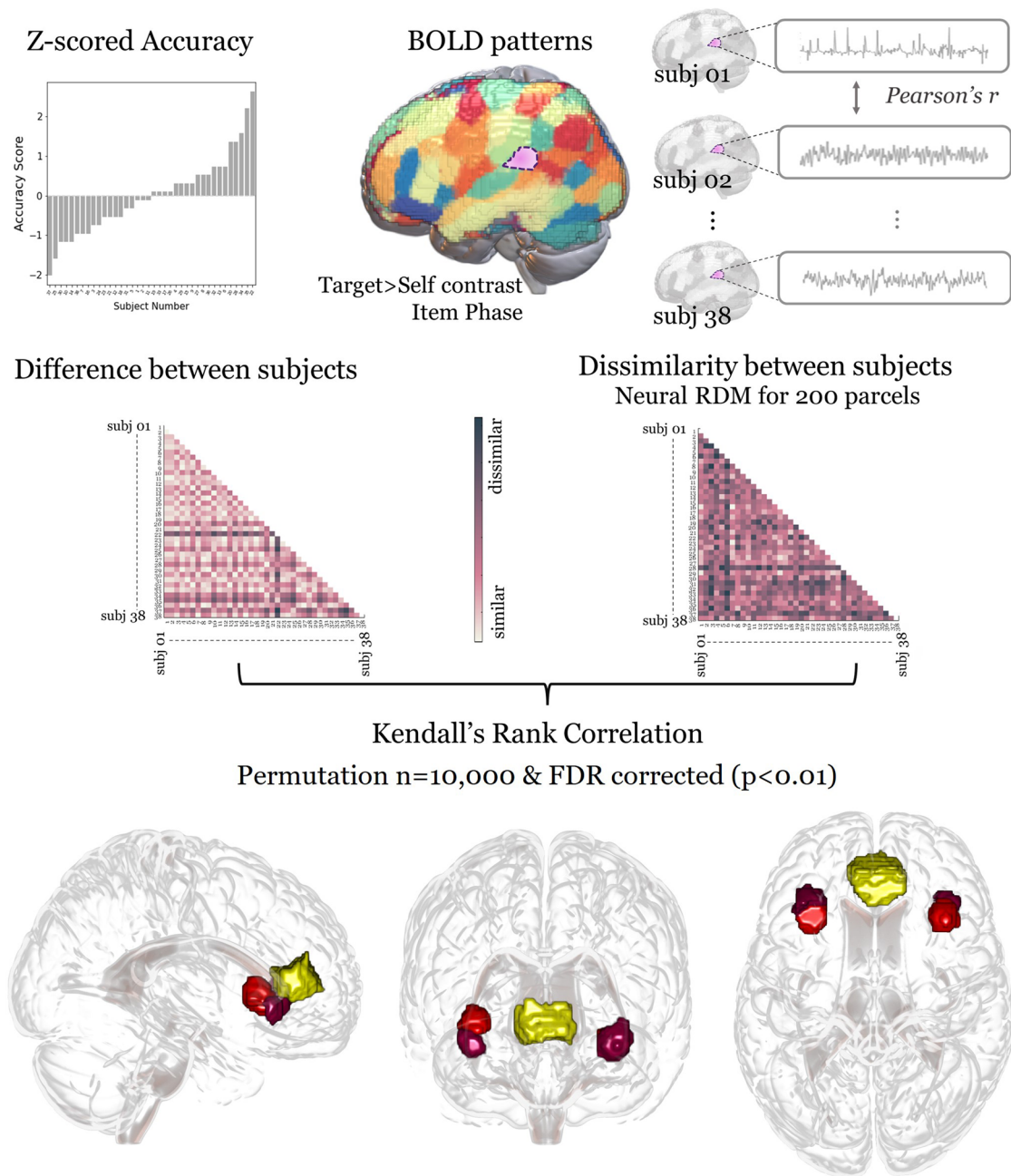


Figure 5. Multivariate results. Inter-subject representational similarity analysis indicates that participants with similar accuracy score exhibited similar neural patterns in brain regions including the pgACC and insula.

However, a recent meta-analysis study suggests that these terms have functioned as 'umbrella terms' encompassing various processes (Schaafsma et al. 2015, Zaki 2017). This has led to inconsistent use of terminology, with different terms being used to describe similar process and vice versa (Schurz et al. 2021). Proposals have been made for a coherent hierarchical model of social cognitive processes, positioning empathy and ToM as higher-order processes. The discussion also advocates for breaking down these processes into smaller, interdependent components through 'deconstruction' (Schaafsma et al. 2015), warranting further exploration of these building blocks. In response, our research aims to contribute as an integral component of this framework. Specifically, our study investigates the cognitive mechanisms involved when individuals infer others' preferences through minimal facial cues combined with contextual information—item cues. Furthermore, we hypothesize

that this cognitive building block is associated with neural activity in the mPFC and the insula.

Roles of dorsal and ventral mPFC subregions in preference estimation

Various subregions of the mPFC, operating in coordination, play a pivotal role in social valuation. A recent model proposes a hierarchical organization of mPFC subregions, with the more dorsal region incorporating additional external sensory information from the environment to regulate the more ventral region, which processes intuitive social values based on internal bodily signals (Kim 2020).

Consistent with the previous study (Kang et al. 2013), our study reaffirmed the role of the dmPFC in estimating others' preferences. The dmPFC is recognized as a key component of the broader

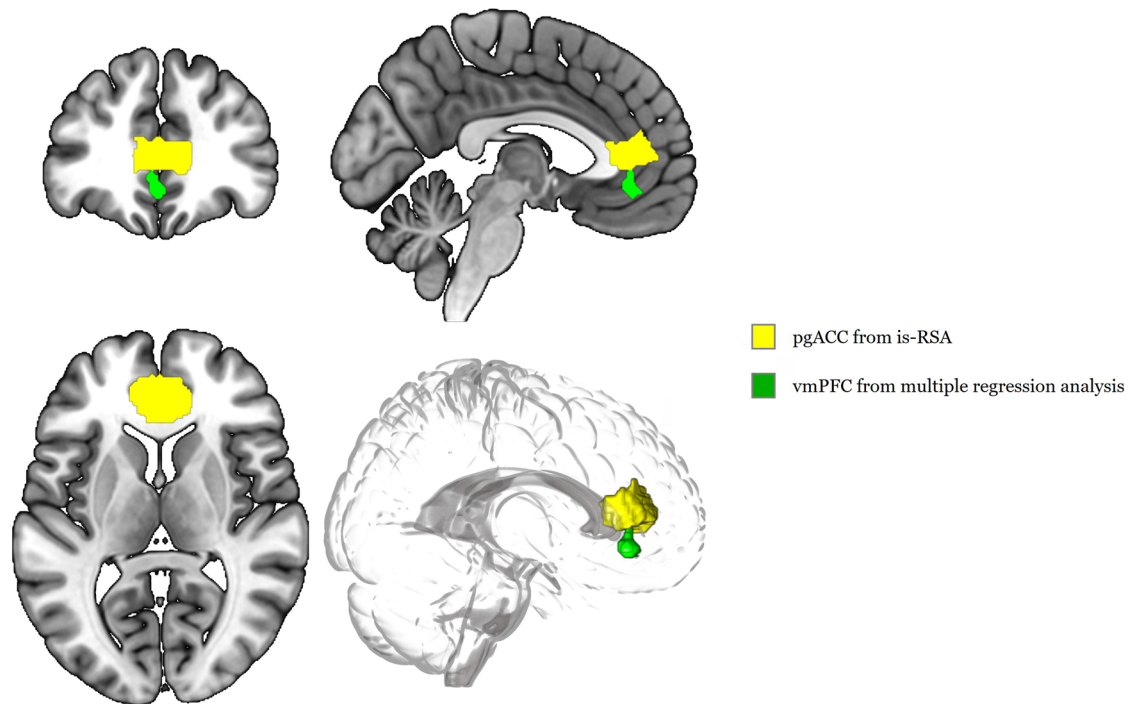


Figure 6. Overlay of results. The vmPFC cluster (green) identified through the univariate approach is combined with the pgACC parcel (yellow) from the multivariate approach.

mentalization network, contributing to a wide spectrum of social processes such as reasoning about other's mental states (Mitchell 2008, Wagner et al. 2012, Wagner et al. 2016), forming impressions of others (Mitchell et al. 2005, Schiller et al. 2009), and predicting social interactions (Powers et al. 2016). Given its role in mentalization, it is reasonable to consider the dmPFC as pivotal in other's preference estimation. Moreover, the dmPFC integrates information from various brain networks to guide thoughts and actions (Shackman et al. 2011), facilitating adaptive responses in a complex social environment.

Contrary to our initial expectations, the ventral region of the mPFC (vmPFC) also emerged as significant in accurately inferring others' preferences. In addition, exploratory gPPI analysis revealed heightened functional coupling between the vmPFC and dmPFC in individuals with greater accuracy scores. This suggests that individuals with higher accuracy scores exhibit increased connectivity between these regions when assessing others' preferences compared to when expressing their own preferences. Drawing from recent theories of morality and altruism (Haidt 2007, Kim 2020), we propose that this phenomenon may stem from an instrumental desire to accurately estimate others' preferences, driven by a primal instinct for survival and reproduction. In other words, individuals may learn that precise predictions foster favourable impressions, leading to the internalization of this instrumental desire within the vmPFC. This facilitates an automatic and intuitive motivation to seek detailed information for preference estimations. This hypothesis aligns with evidence indicating that the vmPFC is involved in context-independent internalized prosocial valuation (Sul et al. 2015, Jung et al. 2018). Considering previous research indicating the association between the vmPFC and self-centred preferences (Kang et al. 2013), individuals with high accuracy in predicting others' preferences may demonstrate increased vmPFC-dmPFC communication, integrating additional external information to resolve conflicts between the instrumental desire for predicting others' preferences and self-centred preferences encoded within the vmPFC (Kim 2020).

Neural representations of pgACC and insula associated with preference estimation

In this study, our *a priori* goal was to uncover the neural patterns associated with accurately estimating others' preferences. Our results showed that individuals with similar behavioural scores exhibited comparable activity patterns in the pgACC and insula, both crucial for interoception—the perception of internal bodily sensations (Critchley and Harrison 2013, Barrett and Simmons 2015). The pgACC and AI are central components of the neural circuitry linked to predicting bodily reactions or maintaining internal equilibrium, potentially through von Economo neurons (VEN), which facilitate rapid brain-body communication (Allman et al. 2010, Fischer et al. 2016). Although this connection suggests a potential link between sensing our own internal states and accurately inferring others' preferences, it remains unclear how the interoceptive network contributes to this process of correctly inferring others' preferences.

The pregenual anterior cingulate cortex (pgACC), in conjunction with the anterior insula (AI), also plays a key role in the processing of social information. The pgACC is actively engaged in tracking others' motivations (Chang et al. 2013, Apps et al. 2016), differentiating between self and other-oriented information in social interactions (Lockwood and Wittmann 2018), and processing empathy (Xu et al. 2009, Wittmann et al. 2018). The activities of the pgACC were positively linked with the ability to utilize contextual information for inferring others' emotional states (Kim et al. 2022), and damage to the pgACC can impede social awareness and empathic capabilities (Seeley 2008). The AI, another critical region, plays a significant role in social information processing and is implicated in empathy, compassion, and various interpersonal phenomena (Lamm and Singer 2010). AI integrates multiple bodily signals to simulate internal states of the targets to generate appropriate empathic behaviours (Singer et al. 2009). Difficulties in theory of mind and hypoactivity in AI during face processing have been noted in autism spectrum disorder (Uddin and Menon 2009). In the

context of social inference concerning the learning of others' preferences, both the pgACC and AI contribute to these complex processes (Lau et al. 2020). Furthermore, individual differences in the activities of the pgACC and AI signify the degree of context dependency in estimating other's affective states (Kim et al. 2022). The extensive involvement of the pgACC and AI in social information processing hints that they may play a coordinating role in predicting preferences in a target individual.

From birth, individuals are deeply intertwined with their primary caregivers for survival, and as they mature, they engage in a dynamic interplay with a broader social environment, shaping and being shaped by it (Atzil et al. 2018). Consequently, individuals develop internal frameworks based on societal norms and the behaviours of those around them. These frameworks shape our 'sense of should' (Theriault et al. 2021), guiding us to act in accordance with cultural and social standards (Constant et al. 2019). Conforming to meet others' expectations can foster a more stable social setting, helping us conserve energy as we navigate the intricacies of social interactions. Previous research has linked the tracking of social norms, aimed at minimizing metabolic costs, to interoceptive processing (Theriault et al. 2021, Sennesh et al. 2022).

Within the framework of interoceptive predictive coding, the brain continually forms and updates models of the external environment and internal organism states (Petzschner et al. 2021, Engelen et al. 2023). Attention plays a pivotal role in modifying these models (Feldman and Friston 2010), prompting individuals to update them in response to prediction errors. Participants who excelled in this task may habitually place significant weight on their social environment, adjusting their generative models more frequently and specifically for each individual encountered. Through consistent attention and adjustment, they likely developed more refined and detailed internal models of others, providing a reliable reference point for more accurate predictions despite task's requirement to predict the preferences of unfamiliar individuals.

This study suggests that that activation patterns in the mPFC and AI are crucial in accounting for individual differences in thin-slicing ability—the capacity to accurately predict others' preferences based on briefly presented facial cues. Given that these regions are key components of the interoceptive neural circuitry, it is plausible that constructing an accurate predictive model of others' preferences—by minimizing the gap between expectations and observed behaviours—requires close communication between the brain and body. Such a refined model could facilitate social interactions, reduce conflicts, and ultimately enhance social adaptability by conserving bodily resources.

Interoceptive network in cue integration

Another noteworthy discovery in this study pertains to the neural patterns in the pgACC and insula, which exhibited variations among participants only during the item phase, not the face phase. This suggests that when facial information was presented, no regions showed neural patterns similar to those of the behavioural accuracy score, implying that estimation accuracy was not contingent upon distinct facial information processing alone. Instead, the critical determinant of preference accuracy appeared to be the integration of both facial and item information, with the insula and pgACC emerging as a pivotal region in this integration process. This finding resonates with previous study identifying the AI's crucial role in cue integration for empathic responses and contextual dependency in ambiguous facial emotion processing (Kim et al. 2022). Conjunction analyses focusing on empathy, interoception, and social cognition have highlighted the AI as a central hub for

integrating interoceptive and social information (Adolfi et al. 2017). Moreover, the communication between the pgACC and AI has been implicated in interoceptive prediction (Barrett and Simmons 2015). Consequently, we hypothesize that both the pgACC and insula play pivotal roles in interoception and social cognition, seamlessly integrating internal and external information to construct sophisticated models of the social environment relevant to an individual's survival goals.

Methodological considerations

This research particularly focuses on the discrepancy between univariate and multivariate analyses. While the pgACC and insula were identified as significant regions in RSA analyses, they were not found in univariate approaches. MVPA is known for its superior sensitivity in detecting subtle differences between psychological states, whereas univariate analysis is more sensitive to inter-subject variability in mean activation across voxels within a specific ROI (Davis et al. 2014, Kohoutová et al. 2020). In support of this, it has been observed that even within the same brain regions, univariate and multivariate analyses can yield opposing results (Woo et al. 2014, Kim and Kim 2021). It has been established that the magnitude of the BOLD response is sensitive to changes in the excitation-inhibition balance within cortical microcircuits, which involve pyramidal projection neurons interacting with local GABAergic interneurons, possibly reflecting mismatch or prediction error-related feedback signals (Logothetis 2008). From this perspective, the dmPFC activity observed in univariate analysis could be interpreted as reflecting the activity of local GABAergic interneurons responding to mismatches or prediction errors arising from the comparison between internal models and external information in the process of inferring others' preferences. In contrast, the pgACC and insula activity observed in multivariate analysis may not be directly related to this preference inference process. While multivariate analysis provides valuable insights into the neural representations associated with individual differences, the lack of convergence across different analytical methods highlights the need for further investigation. Moreover, MVPA, originally developed as a predictive tool, may not always be suitable for interpreting brain function and is more complex than univariate analysis, requiring caution (Hebart and Baker 2018). Future research should employ complementary analytical approaches to better understand the neural mechanisms underlying preference estimation.

The activation patterns of the mPFC and AI were correlated with fine-grained accuracy scores, but not with categorical accuracy. Here, categorical accuracy refers to a coarser measure in which 'like' and 'strongly like' responses are collapsed into a single category, as are 'dislike' and 'strongly dislike.' This distinction emphasizes that the observed neural correlates may be more strongly linked to precise, fine-grained estimations than to broad categorical classifications.

This discrepancy between fine-grained accuracy scores and categorical accuracy scores may stem from the fact that our behavioural task required participants to choose one out of four options rather than simply indicating like versus dislike. A four-choice task likely demands more extensive information processing and mentalization than a two-choice task, potentially engaging different neural circuits. Even if the same neural circuits are involved, the level and pattern of activation might vary. Future research should investigate whether a like versus dislike task would reveal correlations between the activation patterns of the mPFC and AI would and categorical accuracy. Furthermore, this distinction aligns with hierarchical models of social cognition, which propose that higher-order cognitive processes involve complex and

abstract reasoning, whereas lower-order processes rely on faster, heuristic-based decision-making (Schurz et al. 2021). Given that fine-grained judgements require detailed consideration of individuating information rather than broad categorical assumptions, they are more likely to engage neural regions associated with higher-order social inference. In contrast, categorical classification often relies on heuristic processing, allowing for rapid but less nuanced judgments. Our findings, therefore, suggest that the involvement of the mPFC and AI in fine-grained accuracy may reflect the increased cognitive demands of more effortful social inference.

Limitations

This study has a limitation that the participant pool consisted exclusively of female participants. This choice was made to control for potential gender differences in social cognition and preference estimation, as prior studies have indicated such disparities (Carney et al. 2007). However, this limits the generalizability of our findings to a broader population, including males or mixed-gender groups. Additionally, participants may have inferred the targets' preferences based on various pieces of information that can be extracted from their faces (e.g., BMI, facial expression). Future research should aim to include a more diverse sample to improve generalizability and examine which specific facial cues contribute to preference estimation and to what extent.

Furthermore, while our Bayesian post hoc power analysis suggests that the study was likely well-powered to detect the observed effects, we acknowledge that post hoc power calculations based on observed data may provide biased estimates of actual power (Heinsberg and Weeks 2022). These results should therefore be interpreted with caution. Nonetheless, we believe that our significant findings provide credible initial evidence for reported effects. In line with recent study (Lengersdorff and Lamm 2025), we suggest that statistically significant results can retain evidential value even when derived from studies that may not meet traditional power thresholds. Future research should conduct a priori power analyses based on the effect sizes observed in the present study to firmly establish the robustness and replicability of these findings.

Conclusion

In conclusion, this study delved into individual variability in accurately estimating the preferences of strangers based on minimal information. Consistent with prior research, participants overall surpassed chance level estimations, demonstrating a wide range of accuracy scores, with the dmPFC playing a significant role. Notable, activity patterns within the interoceptive network, particularly the pgACC and insula, correlated with similar accuracy scores during the item phase. These findings underscore the neural signatures of individual differences in accurately assessing others' preferences and tailoring estimations to specific targets rather than relying on broad generalizations. We propose that the ability to rapidly infer others' preferences from sparse information serves as a foundational, lower-order process contributing to the more complex, higher-order processes facilitating social cognition. However, further research is needed to elucidate the precise mechanisms of this process in more detail.

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Author contributions

Hyeran Kang (Formal analysis [equal], Methodology [lead], Visualization [lead], Writing—original draft [lead]), Kun Il Kim (Formal analysis [equal], Methodology [equal], Writing—original draft [supporting], Writing—review & editing [supporting]), Jinhee Kim (Formal analysis [supporting], Methodology [equal], Writing—review & editing [supporting]), Hackjin Kim (Conceptualization [lead], Funding acquisition [lead], Project administration [lead], Supervision [lead], Writing—review & editing [lead])

Supplementary data

Supplementary data are available at SCAN online.

Conflict of interest: The authors declare no conflict of interest.

Data availability

To promote transparency and reproducibility, we are committed to sharing our data and analysis scripts upon request. Researchers interested in accessing our data and scripts may contact the corresponding author. We will ensure that all shared materials adhere to ethical guidelines and institutional policies to protect participant confidentiality.

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