The University of Chicago

Functional Connectivity, Risk Assessment, and Emotion Recognition

By

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Abstract

The present paper discusses two experimental designs exploring the relationship between risk assessment and emotion recognition. The first uses publicly available data from the Human Connectome Database preprocessed and parcellated according to the Shen-268 atlas. The proposed second design would use novel data to refine and contextualize the results from the first. The paper proposes an integrative approach to models for human empathy relying on frontosubcortical and motor connectivity. It opens with an exploration of the literature on automatic and cognitive models for empathy. Specific attention is devoted to the overlapping functional networks involved and to the evidence that both pathways have emerged from a need for performance under threat. Both designs are intended to reinforce the argument that functional pathways involved in risk assessment offer a link between automatic and cognitive emotion recognition pathways. For both paradigms, connectome-based predictive modelling is used to predict scores on the HCP gambling task and the HCP emotion recognition task from 7T fMRI data. Separate analyses are conducted for whole-brain and frontosubcortical activity. It is hypothesized that significant nodewise correlations can be used to predict behavior for both tasks in all conducted analyses ($p \leq .01$). In the conducted design, the model did not significantly predict participant behavior on the gambling task or the emotion recognition task. Potential confounds and future directions for empathy research are discussed.

Keywords: empathy, risk assessment, CPM, connectome-based predictive modeling, frontosubcortical, functional connectivity, fMRI, 7T fMRI, HCP, gambling, emotion recognition

Functional connectivity, risk assessment, & emotion recognition

INTRODUCTION

Social cognition forms the backbone of social life. It provides a framework for many of our day-to-day interactions and fosters the connections that drive close relationships. Popular sources make frequent reference to its component processes to explain behavior (Coglianese 2022; Institut national de la recherche scientifique 2022). In order to have these conversations effectively, we must understand the myriad processes that inform social cognitive functioning as well as the structures implicated in each. Despite its importance within psychology and society at large, research on empathy remains divisive. Researchers in different disciplines defend conflicting perspectives on its mechanisms of action. Neuroscience promises to greatly increase understanding in the field, but its methodologies are deceptively seductive in their quantitative results. Functional imaging research has not been immune to many of the same replication issues that plague other domains in psychology. The present paper contextualizes information at the forefront of neuroimaging research with insight from sociological and psychological theory.

The present paper aims to contend responsibly with the neurological, psychological, and phenomenological questions that empathy provokes. The first experimental design analyzes participant emotion recognition, risk assessment, and functional MRI data from an existing open-source dataset in order to establish a solid methodological foundation. I also propose a second design to hone the neuroimaging approach outlined in the first and integrate research insights from across the discipline. This second experimental design would combine behavioral, neuroimaging, and open-ended interview data to provide a comprehensive picture of the relationship between cognitive empathic functioning and risk assessment. Both are driven by recent evidence that young adult functional connectivity can predict individual differences in lab behavior and contextualize broader life outcomes (Finn & Bandettini 2021, Rosenberg et al 2018a; Rosenberg et al 2018b).

Research Design

For the present analysis of the HCP 7T young adult pool, it was hypothesized that resting-state data could train a connectome-based predictive model (CPM) to predict behavior. Participant behavior for analysis was drawn from two measures in the database's battery. The first was a simulated gambling task originally designed to explore striatal BOLD signatures of reward processing (Delgado et al 2000). The paradigm incorporates both positively and negatively weighted blocks and records behavioral measures pertinent to each. As a result, it is well-suited for correlation analyses that consider risk style in both reinforcement and punishment contexts. In the first experimental design, participants' response time for each condition was separately correlated ($p \leq .01$) with whole-brain resting-state functional connectivity to generate a functional connectivity matrix for all 180 participants. The same analysis was conducted for scores on an emotion recognition task (Kohler et al 2003). The measure was originally validated on a sample of patients with schizophrenia and a control pool. It has since been adapted for the general population by the NIMH neuroimaging battery. The HCP Young Adult battery uses this version (Van Essen et al 2013). These correlations were used to train the Yale MRRC Connectome Predictive Model (Shen et al 2017) to predict behavioral results from brain activity. Hypotheses are listed below:

H1: CPM models trained on positive correlation across all 268 nodes would significantly predict increasing response time for both reward and punishment trials in the gambling task;

H2: CPM models trained on negative correlation across all nodes would significantly predict response time for both conditions in the gambling task;

H3: A CPM model trained on positive correlation across all nodes would significantly predict emotion recognition scores on the ER40;

H4: A CPM model trained on negative correlation across all nodes would significantly predict emotion recognition scores on the ER40.

The above hypotheses were repeated using Spearman partial correlation for age category. An ROI analysis was also conducted. To test the ROI-specific research questions, participant brain activity was correlated for only the nodes in the medial frontal, frontoparietal, motor, default mode, limbic, and basal ganglia networks, as defined in the Shen atlas (Shen et al 2017). The four hypotheses listed above were repeated for the ROI analysis using Spearman partial correlation with age category. Every analysis in the present paper uses the same confidence threshold ($p \leq .01$).

Operationalizing Empathy

In its popular use, empathy stands in for a diverse array of social cognitive processes and subprocesses. Researchers strive to adapt this common-sense understanding into an empirically rigorous vocabulary. Most social scientists who investigate empathic phenomena deal with one or a few aspects at a time. Many in the field have pushed for a set of universal terms to communicate results and structure theory more effectively. Because experts with vastly different competencies and interests all have reason to study empathy, the move toward operational congruity is slow and fraught with controversy. The field moves toward consensus gradually in the best cases; it tends to organize itself into contending camps on key issues.

The present paper relies on the most prevalent taxonomy from neuroscientific research. At the broadest level, researchers who use this framework distinguish between automatic and cognitive empathic functions. For much of the past twenty-five years, dialogue has centered around identifying the more central of these two categories. Many researchers study phenomena at large, but others who focus on specific functional or anatomical regions have vested interest in the aspects of a phenomenon that fall within their domain. Both cognitive and automatic elements play clear roles in empathy (Decety 2010). Because each camp has found justifications for opposing models, research has until recently focused on providing evidence to prioritize one theory at the cost of others. Multiple networks play interdependent or simultaneous roles in empathic processing. As a result, understanding other's emotions and interpreting their significance remains a controversial topic in neuroscience. Different schools of thought structure paradigms that focus on radically diverse areas of the brain. The primary camps in empathy research situate their focus either on sensorimotor mirroring or on cognitive representations (Zaki et al. 2009).

Automatic Empathic Processing

On one end, mirror neuron functioning offers a uniquely self-justifying mechanism for empathy. The mirror neuron system spans the premotor, motor, and somatosensory cortices and their connections to the inferior parietal lobe (Redcay & Warnell 2018). Observing another performing a given activity or undergoing a given experience stimulates a subset of the neurons related to performing or experiencing that phenomenon. Rizzolati and colleagues (2004) proposed the mirror neuron system based upon a preponderance of evidence that spans much of neuroimaging's history. EEG studies on slow-wave alpha activity at rest typically delineate between the posterior alpha rhythm (sensory rest) and the central μ rhythm (motor rest). However, evidence from an early movie-watching paradigm demonstrates suppression of both sensory and motor rest rhythms when the subject in the film performs an action (Gastaut and Bert 1954).

Magnetoencephalographic (MEG), transcranial magnetic stimulation (TMS), functional magnetic resonance imaging (fMRI), and electromyographic (EMG) paradigms have all borne out evidence in support of shared motor functional representation (Zaki et al. 2009). These neurons can be mapped with considerable specificity to different motor functions and action plans. Watching someone pick up a ball activates motor neurons specific to that action with those intended results; watching someone hold a ball or go through the motions of picking one up without the ball present activates others. Emotional content, though more complex, creates a somatosensory experience analogous to that of the observed individual. In this way MNS functioning might provide a motor representation that helps us to understand another person's experience.

Most of the early research on the mirror neuron system concerns either pure observation or imitation (Redcay & Warnell 2018). More recent paradigms have introduced social context to explore MNS activation in collaborative and communicative contexts. Some researchers in social neuroscience have proposed explanations for the system's adaptive value based on this evidence (von Hofsten & Rosander 2018). Vicarious somatosensory activation allows information transfer between individuals much more rapidly than is possible with verbal communication. In high-context situations such as performance under threat, MNS activation provides an individual with immediate cues regarding the emotional state and intentions of other actors. The adaptive value of the mechanism is two-fold: it bypasses the need for explicit communication among collaborators, and it offers valuable insight not otherwise available about competitors. A general consensus in the literature emphasizes the importance of past experience in this kind of sensorimotor representation (Redcay & Warnell 2018; Nystrom et al 2011). In order to activate the neurons involved in a specific action or experience, an observation must map onto an available network of established connections. However, infant research has demonstrated alpha desynchronization in similar regions as those observed in adults (Nystrom et al 2011). More research in this area is necessary to better characterize MNS activation in the absence sensorimotor mastery. However, these findings establish the grounds for an integrative feedback loop between past experience, sensorimotor representation, and social cognitive mechanisms.

Despite their promising mechanism of action, MNS models fail to correlate cleanly to behavioral deficits. Studies that attempt to localize MNS activity in response to facial expressions yield mixed evidence (Fan et al 2010). Multiple studies that did find this activation have since had their experimental paradigms called into question. Lesion and dysfunction studies demonstrate that disrupted MNS activity does not uniformly translate into deficits in emotional experience, emotion recognition, or empathy. This inconsistency holds bidirectionally, whether studies select participants based on behavioral dysfunction or physiological differences. Controlling for visual attention and orientation to social cues, individuals with autism and control participants exhibit similar μ suppression in EEG analyses of motor mirroring regions. Given μ waves' established correlation to resting brain states, these findings suggest empathic deficits in autism are not related to mirror neuron function. Existing deficits in social functioning do not necessarily translate into differential MNS activation. Refined methods for localization should be applied to previous paradigms in order to better assess why MNS activation correlates with multiple behavioral measures of empathy.

Though cognitive and automatic processes often occur simultaneously, researchers studying coactivation have encountered mixed results. Some research suggests automatic pathways confer much less empathic accuracy than cognitive pathways (Mackes 2018). Cognitive attribution models situate social orientation in the temporal and parietal lobes as the incipient component of social cognitive judgements (Zaki et al. 2009). Information that activates this pathway triggers activity in the prefrontal cortex (PFC) and orbitofrontal cortex (OFC). These structures offer salience judgements and action plans in conversation with cues from the amygdala and hippocampal information from past experience (Zaki et al. 2009). However, the specific relationship between functional architecture in the frontal cortex and behavioral empathy remains divisive.

Understanding empathic accuracy appears to require a bottom-up assessment of its component functions. As individuals learn and improve performance strategies, they refine context-dependent value judgements that inform attentional shifts towards salient information. Activity in the amygdala can introduce perceptual bias modulated by motivational influences (Kress & Aue 2017). It remains unclear whether the amygdala preferences perceptual attention at a bottom-up level or selects motivationally relevant information at a top-down level (Korponay et al. 2017). Methodological concerns complicate conflicting evidence. Further research must contend with the assumptions inherent in earlier fMRI research while navigating a path forward for social cognitive research. Despite the MNS' incomplete capacity to account for behavior, paradigms exploring activation in these motor neurons have justified its continued consideration (von Hofsten & Rosander 2018). In addition to furthering our understanding of established links between automatic and cognitive processes, researchers going forward should strive to reconcile divergent localizations by seeking new integrative models.

Cognitive Empathy

Paradigms exploring cognitive empathy generally hone their focus on one of several subprocesses. Researchers use 'theory of mind' (TOM) to refer to an individual's ability to attribute agency to other individuals (Cowan et al 2019). At this most basic level, theorists can distinguish between TOM and other phenomena, but the difference blurs as the individual applies it to more complex situations. TOM has been explored in the lab across environmental, facial, and verbal cues. Neuroscientists have localized each of these differently in the brain. In a basic theory of mind experiment, a researcher might ask a participant to observe a confederate in a ball and cup game. The confederate sees the ball placed under a certain cup, but does not see the researcher switch the cups. The participant demonstrates adequate theory of mind if they select the empty cup when asked to identify which one the confederate might believe the ball is under. While TOM is a basic feature of healthy adult functioning, it also forms the basis for higher-order cognitive functioning.

Researchers who study empathic accuracy assess participants' ability to appropriately determine others' mental states from complex situational cues (Eckland et al 2020). Just as empathic accuracy builds on theory of mind, a final aspect of cognitive empathy relies on both that precede it. Researchers concerned with empathic salience investigate the communication between judgment centers, memory centers, and automatic emotional centers (Ashar et al 2017). Ultimately, they aim to determine why and how participants respond to different social cues differently. Each level of cognitive empathic functioning requires sufficient healthy functioning in its constituent processes. Individuals rely on all of them to perform successfully in daily life, so the specific type and extent of impairment may not be clear when someone struggles with empathy on the whole (Decety 2010). Using the established framework, scientists can move up through each level of cognitive functioning to correlate specific patterns of behavior with impairment at a specific level.

Empathy in Context

The neurological mechanisms of empathy have clear evolutionary precedent. Models of human cognitive evolution that subscribe to the "cooperative breeding" theory offer an account of their origins (Silk & House 2016). Early in human history, raising children presented a major liability. The mother would spend nearly a year consuming more than she was able to contribute. Human children also spend far longer than most other animals in a state of dependence. However, the actual resource cost of caring and providing for the mother and child during this period was far less than the opportunity cost of losing a member. Communities which prioritized care for temporarily dependent members were more likely to persist and expand. Evolutionary psychology also offers insight into the links between risk assessment and empathy. The orbitofrontal cortex (OFC), ventromedial prefrontal cortex (vmPFC), and dorsolateral prefrontal cortex (dlPFC) have established roles in identifying and organizing socially relevant information from nonverbal cues (Gold et al 2016). Activation across the mPFC and temporal poles has been shown to predict participants' social value appraisals of faces (in terms of friendliness, empathy, and support) independent of relationships between observers and the observed individuals (Morelli et al. 2018).

These structures likely emerged for the purposes of determining risk. Evidence indicates that vmPFC-amygdala interconnectivity mediates anxiety responses triggered by learned threatening stimuli (Gold et al. 2016). However, connections between the two regions are still developing well into early adulthood. During childhood, high attunement to environmental danger with dampened context-dependent avoidance learning reinforces parental intervention. In context, a cooperative breeding model of development suggests a feedback loop in cognitive evolution. Children who were more sensitive to environmental threat were more likely to survive to self-sufficiency. This tendency, coupled with the limits on their early capacity to learn stable relationships between cues and threats, structured critical community cooperation. Models that focus on automatic processes can also identify roots in evolutionary history. The need to form cooperative social bonds, to have common modes of expression, and to learn by observation drive behavioral mimicry. Just as vicarious motor activation can confer a sense of another's experience for its observer, mimicry fosters familiarity and reciprocal empathy on the part of the other individual (Decety & Jackson 2004). As these behaviors were continually reinforced by survival over generations, early humans developed increasingly complex neural architecture for interdependent social ties. These adaptations allowed for more effective transfer of information and support between individuals.

As greater physical capacities emerge later in youth, connectivity between the frontal areas and automatic networks increases. Changes in frontal architecture predispose greater exploration and independence. However, adolescents compensate with higher attunement to previously dangerous stimuli (Rosenberg et al. 2018a). The mechanisms of this attunement present difficult questions—trait-anxious adolescents demonstrate significant negative vmPFC-amygdala coupling while trait-anxious adults demonstrate significant positive coupling between the same regions (Gold et al 2016). While evolution has carved a channel for these shifts, they can manifest in a myriad of contradictory ways across individuals. Changing frontal-amygdala connectivity during maturation can have impacts ranging from anxiety disorders to risk-insensitive behavioral styles. The architecture involved in socially weighted action planning and cognitive perspective-taking develops much more slowly than that for automatic mirroring and emotional empathy. Frontal structures are some of the last to finish growing– the mPFC in particular does not fully mature until around 25 (Kral et al 2017). In conversation with evolutionary psychology, mirror neuron models might offer an integrative view of empathic development. Behavioral learning and motor mirroring manifest first. These processes set the stage for adolescent and young adult critical periods in frontal development. An individual's vicarious somatosensory representations are modified and reinforced through associative learning. Together, both processes structure emerging higher-order judgment pathways. Fronto-amygdala interconnectivity offers critical elements for a better understanding of the relationship between risk assessment and emotion recognition.

Experimental measures of ASPD and psychopathy have been correlated with reduced white matter fractional anisotropy and increased mean diffusivity in the corpus callosum, right frontal lobe, and inferior fronto-occipital fasciculus (IFOF) (Sundram et al 2011). These findings suggest a twofold explanation for empathy deficits: decreased volume in frontal structures and reduced fronto-limbic connectivity. One proposed model (de Oliviera-Souza et al 2008) views moral cognition as a high-level integrated calculation mainly implicating the PFC, temporal cortex, limbic, and paralimbic systems. The PFC consolidates a context-dependent representation of an event filtered through context-independent social/perceptual frameworks from the anterior and posterior cortex. Activation in the limbic and paralimbic systems assigns context-independent emotional and motivational value to these judgements. PFC impairments impact an individual's ability to interpret situational context and integrate action-guiding information from other regions. Impairments in fronto-limbic connectivity impact the emotional salience attached to situational judgements.

Researchers investigating localizations for empathic phenomena have found compelling evidence by incorporating other functions involved in context-dependent appraisal. Activity in the orbitofrontal cortex (OFC) and periaqueductal gray (PAG) have been correlated with pain anticipation when participants are exposed to pain near the lower threshold of awareness (Brodersen et al 2012). High-threat versus low-threat labeling also significantly predicts participants' perception of pain (Weich et al 2010). Brain activity *before* presentation of a painful stimulus significantly predicts perception. Individuals' contextual judgements seem not only to shape the way they prepare but also the way they experience an event itself. Relationships between experiential encoding processes (for the self) and empathic processes offer strong and comparatively consistent evidence in empathy research (Decety 2010). Greater exploration of prefrontal/orbitofrontal activation in both firsthand and vicarious pain responses may introduce new avenues for integrative research.

Major group differences emerge in imagined pain processing contingent on the perspective required for processing (Decety et al 2013). Individuals who met experimental criteria for psychopathy were actually more attuned to their own imagined pain than the general population. While this hypersensitivity does not necessarily extend to affective experience, it suggests increased pain center/amygdala up-regulation when devoting attention to one's own pain. When imagining others', participants with high scores on the Hare Psychopathy Checklist-Revised (PCL-R) demonstrated reduced activation in the superior temporal sulcus (STS) and mPFC. These results point to uniform mechanisms across populations but suggest differential activation for psychopathic and control individuals. The highest-scoring individuals demonstrated one exception to this trend— apparent positive arousal in dopaminergic areas when attending to visual presentations of another's pain. These results must be explored in similar paradigms.

Behavioral research on automatic processing has demonstrated similar deficits in psychopathy. Both PCL-R scores and prior violent crimes correlate with predispositions against adopting others' perspectives (Drayton et al 2018). Critically, participants with high scores or violent criminal histories did not perform less adequately than controls when specifically asked to adopt another's perspective. Rather, they demonstrated mitigated interference from altercentric information when TOM was not relevant to the task at hand. These findings point to differences in automatic empathic architecture, suggesting that cognitive mechanisms may bridge the gap for goal-directed behavior. The existing literature offers compelling insights into the consolidatory role frontal function plays in empathy. Disorder and injury research will bridge informational gaps in research on normal functioning in order to bolster and refine the model for the present analysis.

Cognitive Empathy: Perspectives from Neuroscience

The OFC and PFC play complex roles in empathic functioning, but key differentiations emerge. Injury research has demonstrated that patients with impairments in either area rate their behavioral empathy significantly lower than controls (Goodkind 2010). However, patients with injuries to the PFC have difficulty making mental state attributions, and OFC patients do not. These findings suggest a major issue inherent to behavioral empathy paradigms that focus on frontal activity— PFC impairments appear to impact the salience, not the accuracy, of empathic judgements (2010). Paradigms sensitive to accuracy alone cannot account for the other ways an individual may struggle to empathize.

Light (2010) offers several useful considerations. The author argues that a large body of work emphasizes what she refers to as *empathic concern* at the cost of other emotions and behaviors that should still be recognized as empathy. "Empathic concern" refers to negative emotional mirroring: pain, fear, sadness, etc. as a response to observing the same emotion. Empathic cheerfulness (displaying positive emotion to improve another's mood after correct identification of negative emotion) and empathic happiness (positive emotional mirroring) need greater construct acceptance and attention in experimental research. While the empathic processing task in the present paradigms deals strictly with emotion recognition, the stimuli presented span the full range of basic human emotion. Overall scores reflect participants' ability to correctly identify positive, negative, and neutral emotions alike. As emotion recognition is a constituent process in higher-level empathic functioning, the results from the predictive analysis can offer insight to structure future explorations that do not overprioritize empathic concern.

Research on antisocial behavior in healthy populations further contextualizes the role of fronto-amygdala connectivity in social cognitive function. Moralizing violent behavior offers a complementary perspective to empathic dysfunction research. The diverse, often diametrically opposed, motivators for different expressions of moral violence complicate mechanistic explorations in research. Two frameworks bear the weight of empirical evidence (Workman et al 2020). The first theory begins in the dorsolateral prefrontal cortex. It argues that moral conviction must overpower cognitive control– decreased dlPFC activity would lead to greater willingness to contradict prosocial norms/drives. The second implicates the ventral striatal/ventromedial prefrontal/amygdala reward network– increased dopaminergic activity in these areas, because of the salience of one's goals or the predicted positive consequences of undertaking them violently. Researchers have also highlighted the dorsomedial prefrontal cortex and temporoparietal junction as loci for self/other information processing– activity here could implicate relative weight of self- and other-oriented considerations (Workman et al 2020).

Cognitive Empathy: Perspectives from Social Psychology

Though healthy humans are innately predisposed to act empathetically, apparent transgressive behavior does not always indicate trait deficit. Evidence from research on violence indicates that reward circuitry does not operate in a vacuum (Bandura et al 1996). The regions involved in reward processing are integrated with those that appraise situational appropriateness. Global identities and attitudes structure loose behavioral frameworks highly sensitive to situational context. In virtual reality situations where participants have a first-person role in violent acts, individuals create different appraisal narratives in "enemy combatant" conditions than they create in "noncombatant" situations (Molenberghs et al 2015). vmPFC activation correlates with the relative congruity of a value judgement to a presented situation. Blunted amygdala activity (in both vicarious violent media presentation and imagined self-activity) suggests less fear or loss-aversive activity when participants consider a situation morally justifiable. However, dlPFC activity suggests that the mechanisms which prime moral violence may occur simultaneously alongside socially salient calculations that would discourage it. Social psychology researchers have further explored these processes to determine the cognitive strategies involved (i.e. in conscious narrative formation). Morally grounded justifications for detrimental behavior override neural pathways for self-censure and inhibition (Bandura et al 1996).

Moral disengagement plays a dual role in behavior– on one hand, it disengages prosocial mechanisms that evaluate other-costs for detrimental actions. When individuals are able to vilify the objects of their antisocial behavior, they free themselves from considerations that might otherwise lead to self-censure (Rai et al 2017). On the other, moral disengagement primes individuals for detrimental or outright violent behavior by heightening their sensitivity to its perceived positive consequences. The OFC and temporoparietal junction regulate prosocial behavior, subjective experience of guilt, and self-directed moral appraisals. The moral justifications an individual makes to explain their violent behavior mitigate experiences of guilt by directly inhibiting activation in these regions (Molenberghs et al 2015). Multiple pathways exist to mitigate the action-guiding empathy a healthy individual feels towards others, further emphasizing the critical role of cognitive empathy in behavior. Researchers must devote careful attention when constructing behavioral empathy paradigms to limit the situational influences that are extraneous to their hypotheses and ensure targeted activation for the specific processes of interest.

Localizations in the Present Analyses

Whole-brain functional connectivity was used for the first battery of hypothesis tests. CPM testing across all 268 nodes allows for the consideration of significantly predictive nodes not anticipated by the analyses that limited testing to the six regions of interest. Predictive patterns not accounted for in the ROI-specific analysis are explored in the Results and Discussion section. The network-specific analyses included the medial frontal, frontoparietal, default mode, motor, limbic, and basal regions. All nodes within each given network were included. TABLE A1 lists the nodes included in each of the ROI networks. Each network included in the analysis is comprised of nodes from multiple areas in the brain. TABLES A2-A4 provide a summary of the nodes that significantly predicted behavior, grouped by network and Yale region designation.

Networks were comprised of nodes in the following Yale-defined regions: Medial Frontal: prefrontal, motor, insula, parietal, temporal, occipital, limbic, subcortical, brainstem (28 total nodes); Frontoparietal: prefrontal, motor, parietal, temporal, cerebellum (34 total nodes); DMN: prefrontal, parietal, occipital, limbic, and cerebellum (20 total nodes); Motor: motor, insula, parietal, temporal, limbic, cerebellum (49 total nodes); Limbic: prefrontal, motor, insula, parietal, limbic, cerebellum (30 nodes); Basal Ganglia: limbic, subcortical, brainstem (29 nodes). As made clear by the number of regions represented in each network and the number of networks each region contributes to, network-based and structure-based functional connectivity analyses offer radically different insights into the relationship between brain activity and behavior.

Proper Methodology in Behavioral Empathy

Empathy research has a particular responsibility to contend with the hard questions that have arisen across the discipline. Many sources publish contradictory findings. The dialogue moves simultaneously in irreconcilable directions as often as it pushes theory towards uniform answers. This profound diversity of opinion drives a greater need for experimental procedures to self-justify comprehensively. Researchers must account for methodological merits and flaws– both in incongruent models and in the literature they build upon for their own paradigms. Major challenges include the usefulness of representative statistical measures, the cross-comparability of fMRI data (parcellation, processing, and bias introduced by collection characteristics), and the difficulty standardizing and comparing between different operationalizations of target behavior.

At its best, statistical research is the gold standard for bridging the gap between theory and evidence. However, it risks offering 'magic bullet' answers for complex problems (Martin 2018). The all-important quest for significant findings can push researchers to statistical methodologies that are highly polished and seemingly self-justifying, sometimes at the cost of more basic structural considerations. Merely conducting a given hypothesis test and regurgitating results prioritizes the answer over the problem. Proper practice in statistics inherently invokes either *a priori* knowledge of the correct model required for analysis or close attention to the strength of the model itself.

This distinction bears little consideration in psychology: empirical research happens for the explicit purpose of testing proposed models. However, its consequences must be considered with caution. Bayesian statistical analysis assesses model fit by leveraging expectations against observed results. In order to properly evaluate 'best fit,' though, we assume that the models being compared are all relatively meaningful explanations of the target phenomenon and then select the strongest among them. If the goalposts aren't set correctly, the relative success of the players tells us *something* about their strengths, but we can only be sure their performance applies in the game the researcher has created. Many familiar examples of this principle first describe correlations between obviously unrelated events only to reveal the confounding variable that links them. The model proposed at the outset fits the results because it describes a real relationship, but it offers no meaningful insight as constructed. One could endlessly refine statistical technique without ever taking account of the assumptions they have allowed in their definition of the variables. If two paradigms both fail to account for the influence of a confounder, the methodological strength of one over the other is meaningless. In fact, a researcher who uses the weaker technique, fails to find the intended result, and returns to the theoretical drawing board is in a stronger place than the researcher who publishes significant findings based on an incomplete account. At this juncture, empathy research must take stock of the crucial ancillary tools available.

Integrating Methodological Considerations

Descriptive organizations of data can offer sanity checks to ensure a paradigm is identifying important– rather than merely significant– effects (Martin 2018). Descriptive statistics offer important insights into the nature of the phenomenon a researcher observes, and they crucially avoid any assumptions in doing so. The general linear model, for instance, is a projection of descriptive data rather than an interpretation. Representations of the data that do not rely on statistical models obviously cannot structure claims or predictions, but they can help to characterize the data in ways that untether our understanding from the heavy burden of statistical best practices. The present experiment will draw on descriptive analysis to provide a window into individual experience and recurrent trends in the group as a whole.

Measures of behavioral empathy have critical merits in statistical research. They allow researchers to delve past socially desirable self-reporting, especially where self-concepts may reflect aspirational attitudes rather than behavior. When structured carefully, they create a means for researchers to measure brain activity in highly specific contexts. However, research on a construct as complex as empathy requires closer attention to the narrative the individual uses to represent their own experience. For one, cognitive empathy is a broad category of phenomena that no one research paradigm can parse out. Even a battery of behavioral tests would give incomplete insight into the mental and emotional experience of a participant. When researchers fail to account for the subjectivity of the people they make claims about, they suffer a cost in understanding (Abbott 2001).

Behavioral measures capture one style of narrative through performance. In their aim to make representations of behavior uniformly comparable across individuals, they strip them of qualitative character and convert them to quantitative scores. Researchers must devote careful attention to justifying the mean measures they use for representative claims between groups or for populations (Speelman & McGann 2013). The mean is not rooted in any actual individual's behavior and likely approximates only a small percentage of the actual scores. Its central status in statistics raises difficult questions. What can we in good faith consider noise? Which measures identify representative values, and which simply reflect a range of responses in which none has any more normative value than another?

These considerations are important, but the issues they raise do not inherently inform alternatives. Statistical comparisons require representative values drawn from quantitative metaphorizations of behavior (and in the case of this experiment, brain activity). In order to rectify the necessity of the mean with its incomplete adequacy, this study will rely on an interview component to introduce individual narratives into the scope of the paradigm. Questions will broadly address self-evaluations of trait empathy, as well as specific theoretical situations aimed to explore cognitive empathy (in other words, an individual's *understanding* of the emotions that a hypothetical other experiences as opposed to action-guiding emotional responses to that understanding). They will then address the specific content of the paradigm, and participants will have the opportunity to contextualize their quantitative performance. These responses will be included in the index to offer full individual narratives as well as the overarching quantitative narrative derived from the data. Participants will be advised that their responses will be made public. They will be asked not to disclose any information they consider identifiable or that they would not be comfortable seeing published.

The inclusion of interview responses also opens another quantitative door. Researchers can rely on factor analysis as a powerful descriptive tool to represent data insightfully without introducing the element of assumptions (Martin 2018). Factor analysis will be used to determine key words and phrases *a posteriori* and correlate these to participant behavioral scores and neuroimaging data. These will not be included in the hypothesis, but they will be helpful for greater understanding of what people who perform differently experience as they empathize. While it cannot structure claims in the same way as the primary analysis, this secondary mode will help inform future directions for research.

The Paradigm

The present experiment explores the mechanisms of empathic accuracy in young adults. It examines functional connectivity at rest and during two behavioral tasks. Brain data will inform whole-brain analyses and specific hypothesis testing for medial frontal, frontoparietal, motor, and subcortical networks. The first task is a facial emotion recognition task (Kohler et al 2003). The second is a gambling task (Delgado et al 2000). Both are included in the HCP young adult functional neuroimaging paradigm (van Essen et al 2013). Performance on each task and accompanying brain activity within predefined regions were used to train a connectome-based predictive model (Rosenberg et al., 2016; Shen et al., 2017) to identify correct responses on the emotion processing task. It was hypothesized that the model would be able to predict behavior significantly better than chance. Intersubject functional connectivity was also determined using a dynamic sliding window model. It was hypothesized that significant frontal connectivity would be found in the target regions.

The second paradigm in the present paper intends to bring broader methodological concerns into focus to foster a strong, ecologically valid exploration of the constructs involved. This component will rely on the same behavioral design as in the original condition. A novel group of participants would complete the gambling task and emotional processing task in the lab. Functional connectivity in the frontal cortex and amygdala would be observed both prior to task performance and while each task is being completed. Data for all participants would be collected on a single scanner and the procedure would mirror that of the HCP dataset to facilitate the most effective replication possible. However, the paradigm features a new interview element to explore relevant analyses not originally conducted in the HCP experiment. The interview data would be used to conduct factor analysis on the content of responses and assess its correlation to performance. Results will provide contextualizing information about individual narratives and experiences not available from the behavioral data. These are expected to provide guidance for future paradigms that explore cognitive empathy and risk assessment.

The present analysis aims to rectify the mirror neuron system model for empathy with frontotemporal/frontoparietal activation theories through an increased understanding of frontal function. The proposed model relies on parallel distributed activation across systems. The first analysis was driven by evidence from prior research that young adult functional connectivity can both predict individual differences in lab behavior and help to contextualize broader life outcomes (Finn & Bandettini 2021, Rosenberg et al 2016). Results from the first experimental design will help appraise and refine the present understanding of social cognition. Significant results would reinforce a bottom-up activation model for social cognition that relies on integrated pathways from limbic structures to frontal areas mediated by parietal and temporal activation. Inconsistencies with the expected results introduce methodological considerations for future research and structure a more theoretically viable model for the neurological correlates of social cognition. Building upon the current literature, the experimental paradigm stands to clarify our operationalizations of important constructs in social cognition and to link the neural mechanisms of risk assessment with those of vicarious emotional appraisal. Notes for further directions will focus on the underlying symmetry between these disparate functions and possible paradigms to parse out their relationship.

The conducted paradigm relies on leave-one-out cross-validation to generate training and test groups for the predictive model. Predictive modelling holdout methods require careful construction that weighs bias against accuracy confidence (Shen et al 2017). Including more data in the training set lowers the bias of the trained model relative to one trained on all available data. Including more data in the test set reduces the variability of error estimates for each iteration (Singh et al 2021). Given larger data pools and effect sizes, a larger test set would be advantageous. The second paradigm suffers even greater constraints to its generalizability than the first due to sample size.

However, it will benefit from the ability to use all participant data in the first resting-state run as the training data and all data from the second as the test data. Because the first analysis only had access to one resting-state run per participant, the CPM code included a modification to prevent cross-set contamination. Rather than input Z-scores directly, groups were created from the array of correlation values. Z-scores had to be calculated for each training set separately. Mean and standard deviation derived from each iteration's training set were used to calculate the Z-score for each test set. While this source of between-groups contamination could be avoided, the influence of family structure could not. Data on shared family structure between participants is only available to researchers with "restricted" or "sensitive" inclusive access to the dataset, so the present analysis was unable to ensure that sibling data was not separated across training and test folds. Novel data collection in the second paradigm would remove this confound.

Downsampling such as that used for the original preprocessing in the HCP pipeline may additionally impact the reliability of some measures in rfMRI. However, functional connectivity and independent component analysis, the crucial analyses for the HCP data, are relatively unaffected (Huotari et al 2019). Ultrahigh magnetic field MR scanners like the Siemens 7T used by the HCP allow for improved contrast-to-noise and greater localization fidelity than is possible in 3T scanning (Glasser et al 2013). Site characteristics are a critical component to consider when arguing for the generalizability of a neuroimaging study's findings (Martin 2017, Horien et al 2021). Because of the specific population biases inherent to research on university students, the paradigm would rely on community outreach, with participation incentivized through nominal compensation (and the prospect of attaining scan images for personal interest). Nonetheless, online methods of outreach to young adults in the Chicago area and the denomination offered would both introduce bias that must be considered.

Novel data collection would, however, offer major advantages to the reliability of findings compared to the present results. Comprehensive demographic data would be collected in order to control for influence from paradigm-irrelevant characteristics. Any especially influential demographic or other confounds identified could be used to structure targeted analyses in the future. Neuroimaging data present a unique set of site biases in their own right, and these deserve proper attention. Site, time of day, time of year, and the specific kind of scanner used all introduce observable bias for fMRI research (Horien et al 2021). The HCP authors controlled for as many of these as possible in the original research (van Essen et al 2013). In addition, head motion in the scanner under the threshold for removal has been known to correlate negatively with certain cognitive assessments (Finn & Bandettini 2021). This correlation is stable across iterations, so it may impact the accuracy of the results more than their reliability. In the second experimental design, head motion would be thresholded for removal and correlated with behavior to determine its impact. Careful attention must also be devoted to the multiple-comparisons corrections used for both the voxel data in both fMRI paradigms and across participants when working with large participant pools (Horien et al 2020). The present analysis relies on leave-one-out cross validation and a p threshold of .01 to account for these influences. The HCP database's inclusion of 7T data represents a strength relative to many similar data pools.

Ultra-high magnetic field fMRI such as the 7T scanner used for the present subset of the HCP data has revolutionized the specificity and reliability with which researchers can record hemodynamic response at the laminar level (Petridou & Siero 2019). Some of the research that laid the foundations for the present analysis predates wide availability of 3T imaging technology at research institutions. The HCP dataset was selected for the present analysis specifically because its authors have pioneered many of the scan techniques and preprocessing pipelines that allow for high-resolution scanning at previously unrealistic repetition times (Ugurbil 2016). Because it prioritizes time-course similarity across voxels, the Shen-268 parcellation scheme is better-equipped for functional connectivity analysis than atlases with anatomic parameters (Rosenberg et al 2016).

DATA AND METHODS

Participants

Participants were 180 young adult individuals (108 female) who completed the HCP Young Adult behavioral battery and the accompanying neuroimaging paradigm. True participant age was restricted by the dataset creators, but age ranges were given as four categories: 22-25 (13.3%), 26-30 (46.1%), 31-35 (39.4%), and 36+ (1.1%). In accordance with the guidelines for access and distribution laid out for public use of the database's resources, more extensive participant demographic information (e.g. ethnicity and relation to other participants in the paradigm) was also not available for this analysis. Exclusion criteria included lack of publicly available 7T resting-state scans, reference to scan quality issues in the database changelog, and failure to complete one of the relevant behavioral measures. 4 individuals (all female) were not included due to partial or total non-completion of the gambling task. No individuals needed to be removed from the analysis for any other reason.

Data Collection

HCP Young Adult Dataset: The Human Connectome Project Young Adult dataset compiles structural and functional imaging data for over 1200 participants across 3T, 7T, and MEG modalities. The dataset has been made publicly available in an unprocessed NIFTI format along with highly processed group average data. In addition to these, individual preprocessed data are available to researchers who request and receive authorization from their home institution and the NIH collaboration network that the HCP falls under. Given the breadth and comprehensive nature of the data, a wide range of processing pipelines and some preprocessed data have been published by other researchers. All data used in the present paradigm were acquired on a 7 Tesla Siemens Magnetom scanner.

Data collection occurred at the University of Minnesota's Center for Magnetic Resonance Research. One scan session totaling 15 minutes of rest data is used for each participant for a total of 900 time points. The original TR of .72s was downsampled to 1s. All participant data was collected using the same echo-planar imaging sequence with an echo time of .0222s and flip angle of 45°. The scanner used a field of view of 208x208mm and a matrix of 130x130, for a spatial resolution of 1.6mm^3 per voxel. Brain imaging data was divided into 85 slices, multiband factor = 5, image acceleration factor = 2, partial Fourier sampling = ⅞, echo spacing = .0064s, bandwidth = 1924Hz/Px. Phase encoding for the analyzed data moved from posterior to anterior.

This paradigm relies on Shen-268 node-parcellated data from the esfinn GitHub repository (Finn & Bandettini 2021, available at GitHub.com/esfinn/movie_cpm). The atlas and the connectome-based predictive modeling (CPM) algorithm derived from it additionally allow researchers to test whole-brain connectivity rather than defining regions of interest *a priori*. The researchers averaged BOLD signals across all voxels within a node for each timepoint. The raw NIFTI data was subject to masking, noise reduction, and the creation and regression of a global signal time series. The files were downloaded by the repository authors in NIFTI format. The data downloaded from the esfinn repository for this analysis was parcellated according to the Shen-268 functional connectome organization. Additional masks were organized in MNI nonlinear space. Alternative pipelines and preprocessed data are accessible within the repository. FIGURES A1.1-A1.3 show the organization of nodes in three representative slices in the 3-dimensional node parcellation.

Gambling Task: Participants were prompted to guess whether the value of a numbered playing card presented to them on a screen would be higher or lower than five. 40% of trials fall into each category, and the remaining 20% end in a 'draw' (card equal to 5). On a win, the participant gains $1. On a loss, the participant has $.50 taken from their earnings. Participants receive the money upon completion. They are not aware that cards are generated *a posteriori* based on response, or that every participant receives the same amount over the course of trials.

Emotion Recognition Task: The Penn Emotion Recognition task (Kohler et al 2013) presents participants with 40 faces displayed on a monitor consecutively. For each, the participant is asked to identify the emotion displayed as happiness, sadness, anger, fear, or disgust. Participants are given three seconds to respond. Scores are recorded as a sum out of 40 possible correct identifications. The measure is validated for use with both psychiatric populations and healthy adults.

Methods

The present paradigm relied on a publicly available git repository for scan data. Variables for posterior-anterior resting-state data were drawn from the 7T scans for all 180 participants in the esfinn repository (Finn & Bandettini 2021) who completed both the gambling task and the emotion recognition task. In addition to standard processes of elimination based on quality control notes in the update log, the present paradigm also required participants to have full Penn Emotion Recognition Task and gambling task scores accessible publicly on the HCP Young Adult website itself. These were downloaded from the unrestricted behavioral data dump on the database website. Participant behavioral scores were made available in aggregate (individually, but not divisible into performance on specific questions or the subscores outlined in the NIH guidelines for each task). Behavioral scores used for predictive modeling included: individual median response time during gambling task reward trials; individual median response time during gambling task punishment trials; individual total score on the Penn ER40 task; individual median response time across all trials in the ER40.

The dataset divided brain organization into the ten broad functional networks outlined above. Empirical research has consistently validated the Shen268 atlas for delineations of functional architecture in novel participants (Shen et al 2017; Rosenberg et al. 2018b; Finn & Bandettini 2021). Functional connectivity, at the level of individual connectomes and whole functional ROIs, offers a strong basis for predicting individual behavior based on task, rest, or other versions of rest-like data collection. The downloaded data were individual 2D tables of connectivity values for each of 180 participants with dimensions of 900 time points (1s per time point for a single 15-minute resting-state scan) x 268 nodes. The data were converted to .mat double array files for analysis. All participants' two-dimensional data (node and time point) were combined into a single three-dimensional array grouped by participant along the third dimension. The correlation coefficient for each participant's activity across all 268 nodes was calculated. This value was used to derive the z-score for each participant. Node self-correlation was assigned a default value of one to remove perfect correlations from the resultant matrix. FIGURES A2 & A3 show functional connectivity in the regions of interest organized by network (FIGURE A2) and region (FIGURE A3).

The Fisher z-transform of each training set participant's resting-state correlation matrix was fed to the Yale MRRC CPM downloaded from the lab's GitHub repository at github.com/YaleMRRC/CPM. The Fisher z-transformed connectivity matrix provides edge (node x node functional connectivity) values for correlation with behavior. CPM first conducts a correlation test to determine the relationship between edgewise values and behavior. Because the data are not normally distributed, a Spearman correlation was performed. The algorithm uses the *a priori* p-value input (.01) to discriminate edges that do and do not significantly predict behavior within each participant's connectivity matrix. Statistically significant edges are subdivided into positive and negative categories. The sum of values for each category provides a vector to train separate predictive models for positive and negative correlations. The array of predictive values is then compared to a null dataset consisting of random permutations of the real data. Leave-one-out cross-validation and a p-value of .01 were used to account for the large number of comparisons run in fMRI analysis. For all 180 iterations, individual data for one participant was removed from each analysis to test against the model trained on all others. The null predictive algorithm performed identical analyses on a new random permutation for each iteration. For the network-based analysis, the medial frontal, frontoparietal, default mode, motor, limbic, and basal networks were isolated from the whole-brain array. Each participant's data was time-series averaged and nodes were correlated as in the previous analyses.

The proposed second experimental design would be completed on the same scanner in blocks of back-to-back days. Each participant group would complete all components in a single day. This design would recruit novel participants ($n \leq 40$) between the ages of 18-35 for an fMRI paradigm repeating the tasks from the HCP dataset. Extensive demographic data would be recorded to more specifically assess and control for confounding effects. Age plays a particularly important role in frontosubcortical connectivity. This paradigm would incorporate partial correlation between behavior and brain activity modulated by age to account for the changing structure of the brain across adolescence and early adulthood. In the first paradigm, the partial correlation could only incorporate four age categories. The second paradigm would evaluate age as a discrete variable by month. Inclusion criteria would require participants to be between 18-35 years old with no history of traumatic brain injury, psychiatric hospitalization, or neurophysiological illness. The paradigm would recruit from the general population. The participant pool size is derived from variance considerations that are especially relevant in predictive testing using fMRI data (Shen et al 2017).

Neuroimaging datasets of any size pose difficulties in recruiting, data collection expenses, and time/resource costs inherent to data processing. Bins of ~10 participants in each category represent a compromise between statistical responsibility and practical achievability. Leave-one-out intersubject functional connectivity analyses grouped by age (18-21,22-25,26-30,31-35) would be aimed to contribute to the understanding of functional connectivity profiles at rest. Functional matrices would be summed across timepoints and participants to derive a representative matrix for each group and the pool as a whole. A leave-one-out CPM would also be conducted for each age group to determine how impulsivity and emotion recognition manifest across the lifespan.

Participants would complete the interview component after completing both sets of tasks and the scan protocols. The initial questions would relate directly to the tasks themselves. They are intended to relate personal experience to performance. The questions would iterate through the elements of both tasks before turning to the participant's daily life. As noted, they would be advised not to disclose sensitive information or anything they would rather not see published in the factor analysis. These questions would be structured to briefly explore the lifestyle, habits, and personality underlying the constructs that try to approximate them. Factor analysis would help identify common themes for age groups and predetermined performance categories based on the distributions in the present data. These would not be included in any hypothesis testing, but would serve to inform related paradigms that can more capably target risk assessment and emotion recognition in the lab. In addition, they would be included in the discussion to weigh in against the findings and determine how the quantitative data reflects individual experience. The proposed open-ended interview and consent form are attached in APPENDIX B.

The CPM function creates arrays of all r and p values across all timepoints and identifies values in that meet the threshold for inclusion. Values are converted into binary format for each edgewise correlation (0 if not included; 1 if included). These are stored as negative and positive masks (Shen et al 2017). For the whole-brain hypothesis test, the matrix of r and p values for each iteration was stored in an array, averaged, and thresholded to derive representative masks. Using the network visualization software available through the Yale CRRPM BioSuiteWeb connectivity viewer (bioimagesuiteweb.github.io/webapp/), these average masks were visualized on circular node-path networks. To visualize the most concentrated internetwork connections, only nodes with ten or more significantly predictive edges are included. FIGURES A7-A9 show these node-path networks.

RESULTS

Whole-brain CPM analyses using Spearman ranked correlation did not significantly predict overall gambling response time during punishment trials, response time during reward trials, or ER40 score from resting-state functional connectivity. The resulting p and r values are listed separately for positive nodes and negative nodes. Whole-brain partial Spearman correlation including age range (4 categories: 22-25; 26-30; 31-35; 36+) was conducted. This correlation also yielded results that did not reach the level of significance. Partial Spearman correlations were also used for the network-based analysis. These correlations also did not reach significance. All results are illustrated in TABLES 5-7 below.

Tables 5-7

Table 5: CPM Performance for the Gambling Task (Reward Trials)

	Whole Brain (Spearman)	Whole Brain (Partial)	ROI (Partial)
Neg:	r = .1840, p = .0134	r = .1199, p = .1088	r = .0637, p = .3955
Pos:	r = .0905, p = .2269	r = .0254, p = .7352	r = -.0306, p = .6837

Table 6: CPM Performance for the Gambling Task (Punishment Trials)

	Whole Brain (Spearman)	Whole Brain (Partial)	ROI (Partial)
Neg:	r = .0549, p = .4643	r = .0095, p = .8994	r = .0875, p = .2426
Pos:	r = .0017, p = .9817	r = -.0734, p = .3276	r = -.0675, p = .3657

Table 7: CPM Performance for the ER40

	Whole Brain (Spearman)	Whole Brain (Partial)	ROI (Partial)
Neg:	r = .0831, p = .2676	r = .0905, p = .2268	r = .1283, p = .0860
Pos:	r = .0035, p = .9627	r < .001, p = .9968	r = .0361, p = .6305

CONCLUSIONS

The data do not support the hypothesis that resting state functional connectivity significantly predicts response time during reward or punishment trials on the gambling task, or that it predicts total score on the ER40. Some effects that did not reach significance are notable. Whole brain activity Pearson correlation demonstrated an effect size above r = .1 at a p-value just above the threshold for significance on reward trials for the gambling task. Whole brain activity partial correlation with age also demonstrated predictive power above r = .1 for negative nodes in the reward trials of the gambling task. However, the effect for partial correlation with age is smaller than for the analysis that does not consider age. This suggests that age contributed confounding predictive power for reward trial response time in the gambling task. Given that both models trained on whole-brain activity for the reward trials demonstrated higher predictive power and confidence than the ROI-based model, future paradigms can specifically explore network connectivity in networks not included for the present ROI analysis. Task-based analyses may more adequately predict risk assessment from frontosubcortical activity.

The opposite trend appeared for the ER40, suggesting that resting-state frontosubcortical activity deserves specific attention in emotion recognition. ROI activity partial correlation with age demonstrated predictive power above r = .1 for negative nodes in the ER40. TABLES A2-A4 show the number of edges across the whole brain (partial Pearson analysis) that significantly correlated to behavior, grouped by network and region, for each task. FIGURES A4-A6 show these nodes organized into correlation matrices. FIGURES A7-A9 show internetwork connectivity for high-degree nodes (those with at least 10 edges significantly correlated with behavior) in each task. Barring visual networks necessary for processing of visual stimuli, the motor, basal ganglia, limbic, and medial frontal networks contributed the most nodes that significantly correlated with behavior for the ER40. The motor, medial frontal, basal ganglia, and frontoparietal networks contributed the most for gambling reward trials. The motor, limbic, frontoparietal, and medial frontal contributed the most for reward punishment trials. Notable trends include: frontosubcortical correlation with behavior across all tasks; the differential priority of basal ganglia and limbic networks between gambling conditions; and the role of the motor network in both tasks. These trends indicate support for existing literature and point to possible links for future analysis.

Bias may have been introduced into the resting-state fMRI data by the fact that the HCP Young Adult dataset relies heavily on twin and sibling data. Future research would do well to revisit the premises of the paradigm with resources that would mitigate its limitations, especially restricted demographic access. Requests for time-series task fMRI data where available would also allow for event-related analyses. Access to raw participant data would allow direct control for scanner bias, head motion, and life characteristics that was not possible in the conducted design. It would also open the door for alternative preprocessing pipelines and data organizations.

By aligning themselves *alongside* scientific modes of analysis and taking nothing for granted in their claims, humanist approaches often pay a fuller respect to the complexity of their work than their counterparts in psychology. In their zeal to earn their discipline's place under the banner of 'hard science', psychological researchers can create cultishly opaque modes of theory-generation that unintentionally situate their claims adjacent to truth. The present paper aims for an experimental design that restores human character to human behavior. The values derived from individual interviewing would allow for analysis based on group narratives of experience in addition to the usual process of construct metaphorization and validation. Careful attention to the assumptions inherent-- in both the conducted and proposed designs-- can temper their findings and inform future experimental design. Social cognitive and automatic processes play complex and interdependent roles in the behavioral tasks. Participant responses would offer crucial perspective in generating claims from their findings. The ability to control for participant family status, age in years, and to assess scan quality directly will improve the quality of the analyses possible.

Continuing research will leverage improvements in structural and functional imaging to more conclusively demonstrate the relationship between risk assessment and emotion recognition—especially the controversial role of the MNS. Neuroimaging methodologies improve rapidly in tandem with the technologies they rely on. Functional connectivity analyses themselves are novel by comparison to most disciplines in psychology. These improvements can strengthen integrative approaches by paring down the number of factors at play in incongruent findings. More research should also focus on the role that frontoparietal activation plays in integrating moral and empathetic information into judgment. The OFC's activity in risk-reward assessment and its connections to the insula and amygdala could inform models based in maladaptive personal risk-taking styles and inadequate outcome prediction mechanisms that extend beyond the self. Many existing models, the present included, emphasize the role of dominant edges in network function. However, in densely connected regions, redundancy may play an important role in successful function. As illustrated in the connectivity matrices, frontal networks have dense activation profiles even at rest. Future paradigms could explore claims considering the densest networkwise connections rather than the most active nodewise connections. More attention is also needed to the role of the amygdala for motivation-dependent attentional bias. Empathy research would benefit from a greater understanding of which frontolimbic pathways are involved in evaluating threat and which orient attention toward positively valenced salient features. These considerations will all help to structure refined integrations of automatic and cognitive empathic function. Pathways for risk and reward evaluations will play a key role in that effort.

No one pathway can comprehensively explain the emergence of empathy in humans or the structural anomalies that result in dysfunction. Automatic emotional mirroring offers alluring insights into the mechanisms of shared emotional experience, but research must carefully weigh these aspects of empathic phenomena against established cognitive pathways. By the same token, deprioritizing the automatic components– especially systems as unique in function as the mirror neurons– risks setting aside major avenues towards understanding the mind. MNS activation maps observation to previously established sensorimotor pathways, but infant paradigms suggest that activation does not require motor mastery. Observation activates available networks to convey a degree of information about the observed action or experience. This information structures learning by engaging component and emerging pathways automatically. Frontal networks integrate prior experience with somatosensory and subcortical information to facilitate conscious judgements regarding others' emotional states and somatosensory experiences. Evolutionary models for each of these pathways confer a better understanding of why and how empathy has developed its central role in human social and neurological function. Both indicate close ties between the emergence of risk assessment and emotion recognition. While the results in the present paradigm did not support the hypotheses, the convergence between risk assessment, emotion recognition, and automatic somatosensory representation remains important for empathy research.

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APPENDIX A

Appendix A includes all supplementary tables and figures relevant to the conducted analyses in the first experimental design. Tables and figures that show a given representation organized separately for each task are generally presented together on a single page. Tables 2-4 are an exception due to their length: these are presented on three consecutive pages preceded by a preface and legend describing them.

Figures A1.1-A1.3

Networks in the Shen-268 Atlas

Figure A1.1: Shen Atlas, Coronal

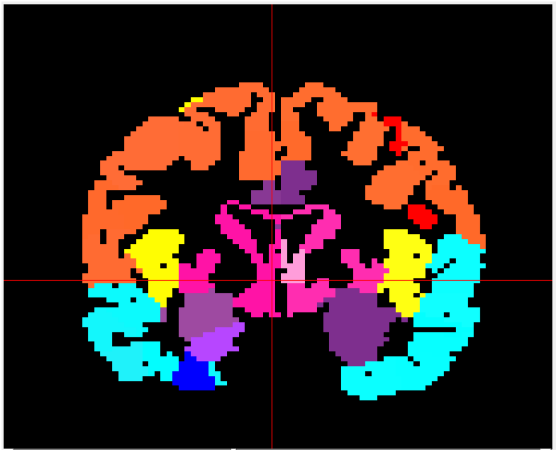


Figure A1.2: Shen Atlas, Sagittal

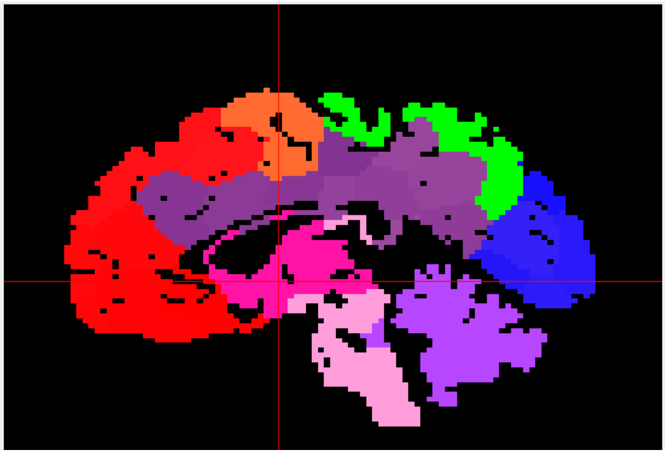
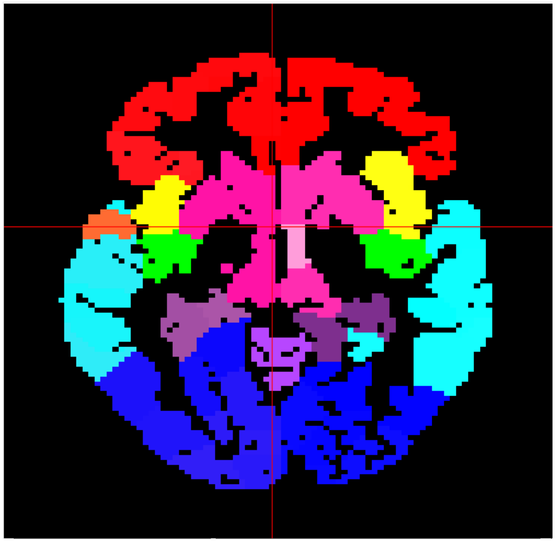


Figure A1.3: Shen Atlas, Axial



Note. Visualized in MATLAB from a NIFTI image available on the esfinn database. Colormap values modified to match network organization. Nodes are ordered by hemisphere, such that the right hemisphere encompasses nodes 1:133 and the left hemisphere encompasses nodes 134:138. Note unequal distribution across hemispheres.

Legend:

Prefrontal:	1-22, 134-157	Red
Motor:	23-33, 158-167	Orange
Insula:	34-37, 168-170	Yellow
Parietal:	38-50, 171-184	Green
Temporal:	51-71, 185-202	Cyan
Occipital:	72-82, 203-216	Blue
Limbic:	83-99, 217-235	Dark Purple
Cerebellum:	100-119, 236-256	Bright Purple
Basal:	120-128, 257-264	Magenta
Brainstem:	129-133, 265-268	Pink

Table A1

Frontal and Subcortical Regions in the Shen-268 Atlas

Network	**Nodes**
Medial Frontal	10, 12, 52, 53, 54, 56, 57, 64, 65, 137, 140, 145, 148, 149, 150, 151, 153, 156, 162, 165, 183, 185, 186, 187, 190, 192, 194, 219
Frontoparietal	1, 4, 7, 8, 9, 14, 16, 17, 19, 21, 22, 30, 31, 47, 48, 55, 70, 111, 112, 116, 139, 142, 143, 154, 157, 164, 182, 184, 193, 196, 199, 242, 246, 247
DMN	3, 5, 6, 13, 49, 50, 85, 86, 90, 96, 115, 134, 138, 141, 203, 222, 223, 225, 227, 239
Motor	23, 24, 25, 26, 27, 33, 34, 35, 37, 38, 39, 40, 45, 46, 51, 58, 60, 61, 62, 63, 84, 89, 92, 97, 109, 158, 159, 161, 163, 166, 167, 168, 170, 171, 172, 173, 174, 179, 180, 181, 188, 189, 191, 195, 197, 202, 218, 228, 235
Limbic	2, 11, 15, 20, 28, 29, 32, 36, 44, 83, 88, 91, 110, 119, 135, 136, 144, 146, 152, 155, 164, 178, 220, 221, 224, 226, 244, 245, 251
Basal Ganglia	93, 94, 95, 96, 99, 120, 121, 122, 123, 124, 125, 126, 127, 128, 217, 229, 230, 231, 232, 233, 234, 257, 258, 259, 260, 261, 262, 263, 264, 265

Note. Node numbers <134 denote nodes in the right hemisphere. Node numbers >133 denote nodes in the left hemisphere.

Figures A2-A3

Region-Of-Interest Functional Connectivity Matrices

Figure A2: ROI Functional Connectivity by Network

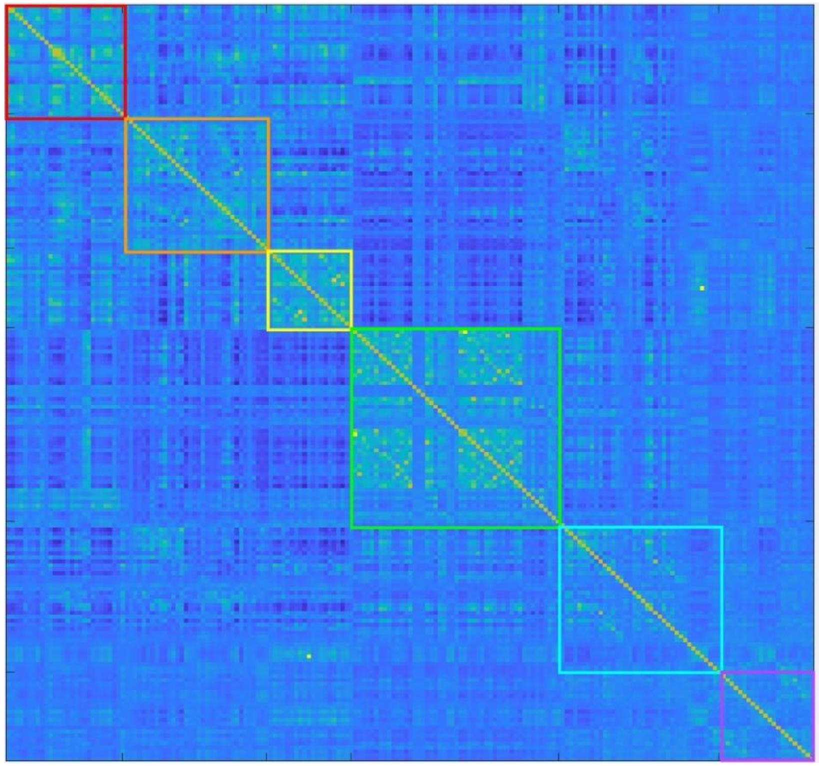
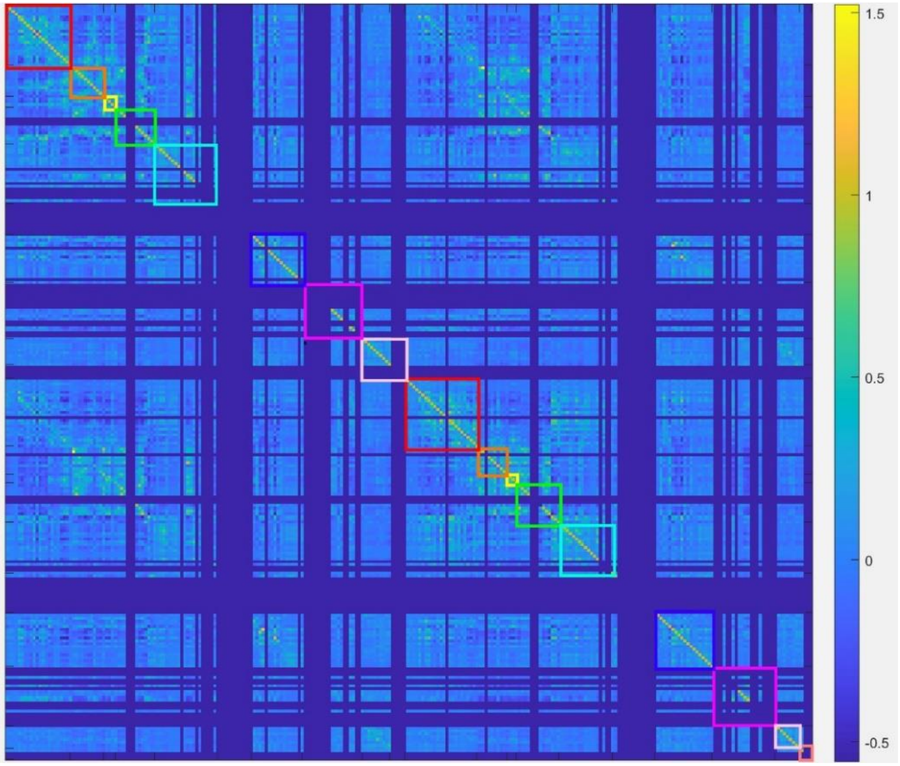


Figure A3: ROI Functional Connectivity by Region



Note (Figure A2). Reorganized so all nodes in each network appear consecutively. Network self-correlation highlighted. Ordered as follows: medial frontal (red); frontoparietal (orange); DMN (yellow); motor (green); limbic (blue); basal ganglia (purple). Colors in matrix correspond to Z-score colormap at far right. Yellow areas represent notable positive correlation; lighter blue areas represent little or no correlation; dark blue areas represent negative correlation.

Note (Figure A3). Connectivity matrix organized in node order; regional self-correlation highlighted. Ordered as follows: prefrontal (red); motor (orange); insula (yellow); parietal (green); temporal (light blue); limbic (dark blue); cerebellum (magenta), basal ganglia (light pink), brainstem (pink). Matrix color values for nodes not included in ROI analysis rendered as dark blue. Matrix color values for ROI nodes correspond to those in FIGURE A2.

Tables A2-A4

Number of Edges Significantly Correlated with Behavior

The following tables display all nodewise connections (edges) that significantly correlated with behavior in each task. Edge totals are summed for each of the ten networks defined by the Shen atlas (Shen et al 2017). Because the Yale network assignments rely on functional connectivity, individual nodes within the same network may be localized to several regions across the entire brain. Regional totals are included for each network. Networks with no significantly predictive edges for a given task are not included.

Legend: (R-/L- denotes lateral location)

Lim (Limbic)

Bst (Brainstem)

Par (Parietal)

Tem (Temporal)

Cer (Cerebellum)

Pre (Prefrontal Cortex)

Mot (Motor Cortex)

Occ (Occipital)

Table A2

ER40: Number of Edges Significantly Correlated with Behavior by Network and Region

Network	Region	Significant Connections*
Basal Ganglia	L-Lim	9
	R-Lim	9
	L-Sub	8
	R-Sub	6
	Basal Ganglia Edges	32
Cerebellum	R-Cer	6
	L-Cer	5
	Cerebellum Edges	11
Default Mode	L-Lim	6
	R-Lim	6
	Default Mode Edges	12
Frontoparietal	R-Pre	7
	Frontoparietal Edges	7
Limbic	L-Cer	9
	R-Lim	7
	R-Mot	6
	L-Lim	5
	Limbic Edges	27
Medial Frontal	L-Lim	9
	L-Pre	7
	R-Pre	7
	Medial Frontal Edges	23
Motor	L-Par	17
	L-Tem	14
	R-Tem	9
	R-Mot	8
	R-Lim	6
	Motor Edges	54
Visual Association	L-Occ	16
	L-Tem	8
	R-Tem	6
	Visual Association Edges	30
Visual I	L-Occ	5
	Visual I Edges	5
	Total Predictive Edges	201

*p<.0

Table A3

Gambling (Reward): Number of Edges Significantly Correlated with Behavior by Network and Region

Network	Region	Significant Connections*
Basal Ganglia	R-Lim	10
	R-Sub	10
	L-Bst	9
	L-Lim	9
	Basal Ganglia Edges	38
Default Mode	L-Lim	15
	L-Pre	12
	Default Mode Edges	27
Frontoparietal	R-Cer	23
	R-Pre	15
	Frontoparietal Edges	38
Limbic	R-Mot	13
	R-Lim	12
	L-Pre	9
	Limbic Edges	34
Medial Frontal	L-Pre	21
	L-Lim	14
	L-Tem	9
	Medial Frontal Edges	44
Motor	L-Tem	21
	R-Mot	21
	R-Lim	11
	Motor Edges	53
Visual I	L-Occ	10
	Visual I Edges	10
Visual II	L-Occ	29
	R-Cer	14
	Visual II Edges	43
Visual Association	R-Tem	41
	L-Occ	14
	L-Tem	10
	Visual II Edges	65
	Total Predictive Edges	352

*p<.01.

Table A4

Gambling (Punishment): Number of Edges Significantly Correlated with Behavior by Network and Region

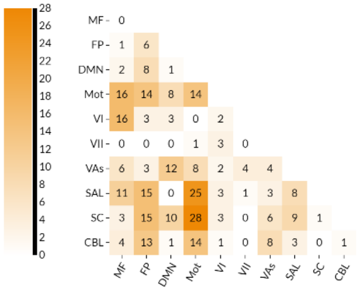
Network	Region	Significant Connections*
Basal Ganglia	R-Lim	13
	Basal Ganglia Edges	13
Cerebellum	L-Cer	10
	R-Cer	7
	R-Bst	6
	Cerebellum Edges	23
Default Mode	L-Pre	8
	Default Mode Edges	8
Frontoparietal	R-Pre	23
	L-Par	8
	R-Cer	8
	Frontoparietal Edges	39
Limbic	R-Mot	17
	L-Pre	16
	R-Pre	8
	L-Lim	8
	Limbic Edges	49
Medial Frontal	L-Lim	11
	L-Pre	10
	L-Tem	8
	L-Mot	6
	Medial Frontal Edges	35
Motor	R-Mot	25
	L-Tem	1
	L-Mot	11
	L-Par	6
	Motor Edges	56
Visual Association	L-Tem	18
	L-Occ	14
	R-Tem	7
	Visual Association Edges	39
Visual II	R-Cer	6
	Visual II Edges	6
	Total Predictive Edges	268

*p<.01.

Figures A4-A6

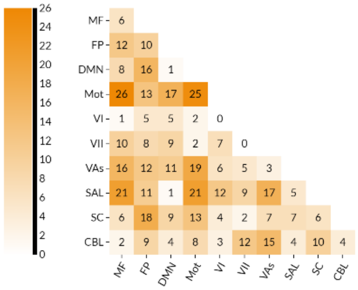
Edgewise Correlations by Network

Figure A4: ER40



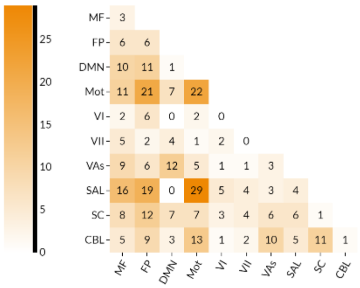
	MF	FP	DMN	Mot	VI	VII	VAs	SAL	SC	CBL
MF	0									
FP	1	6								
DMN	2	8	1							
Mot	16	14	8	14						
VI	16	3	3	0	2					
VII	0	0	0	1	3	0				
VAs	6	3	12	8	2	4	4			
SAL	11	15	0	25	3	1	3	8		
SC	3	15	10	28	3	0	6	9	1	
CBL	4	13	1	14	1	0	8	3	0	1

Figure A5: Gambling Reward



	MF	FP	DMN	Mot	VI	VII	VAs	SAL	SC	CBL
MF	6									
FP	12	10								
DMN	8	16	1							
Mot	26	13	17	25						
VI	1	5	5	2	0					
VII	10	8	9	2	7	0				
VAs	16	12	11	19	6	5	3			
SAL	21	11	1	21	12	9	17	5		
SC	6	18	9	13	4	2	7	7	6	
CBL	2	9	4	8	3	12	15	4	10	4

Figure A6: Gambling Punishment



	MF	FP	DMN	Mot	VI	VII	VAs	SAL	SC	CBL
MF	3									
FP	6	6								
DMN	10	11	1							
Mot	11	21	7	22						
VI	2	6	0	2	0					
VII	5	2	4	1	2	0				
VAs	9	6	12	5	1	1	3			
SAL	16	19	0	29	5	4	3	4		
SC	8	12	7	7	3	4	6	6	1	
CBL	5	9	3	13	1	2	10	5	11	1

Note. Matrices show total number of significant edgewise correlations between each network (including within-network correlations) that significantly correlated with each behavior. Network labels listed on both axes correspond to legend below. Color denotes number of significant edges corresponding to colormap accompanying each matrix.

Legend:

MF = medial frontal
DMN = default mode network
VI = visual cortex I
VAs = visual association
SC = subcortical
FP = frontoparietal
Mot = motor
VII = visual cortex II
SAL = limbic/salience
CBL = cerebellum

Figures A7-A9

Inter-Network Connectivity that Significantly Correlated with Behavior

Figure A7: ER40 Network Interconnectivity

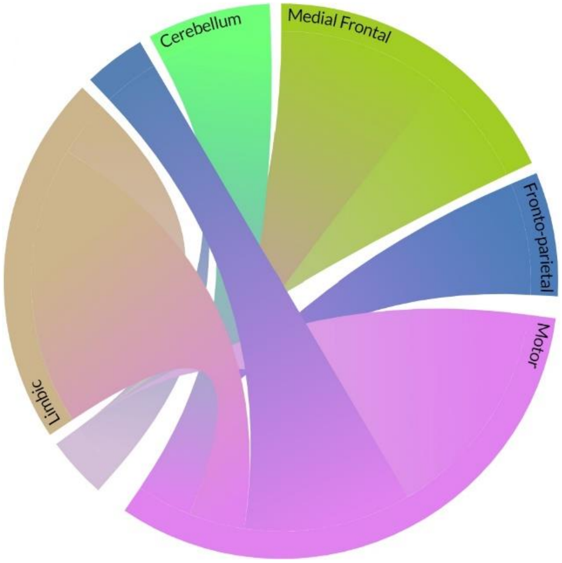


Figure A8: Reward Network Interconnectivity

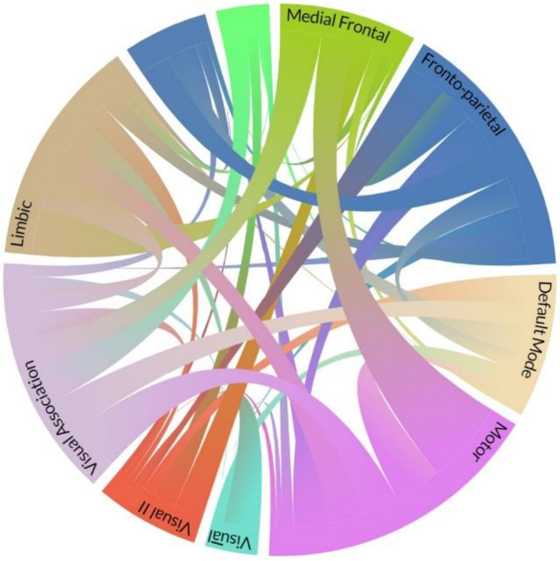
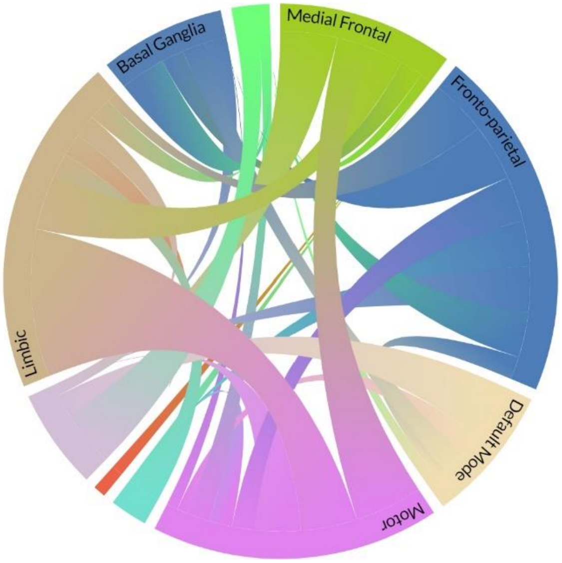


Figure A9: Punishment Network Interconnectivity



Note. Size of each network and each branch denotes number of edgewise correlations that significantly correlated to behavior. Node degree thresholded at 10 (only those nodes with at least ten significant edgewise correlations are displayed). Correlations between nodes within each individual network are not represented.

*p value < .01.

APPENDIX B

Appendix B1: *Informed Consent Form for Proposed Second Experimental Design*

Appendix B1 shows the informed consent form that would be presented to participants for consideration before the interview portion of the second experimental design. It outlines terms of data storage, continuing consent, and the ways that participants' verbal responses might be used in publication if they choose to take part.

Note. Informed consent for the interview portion is included in the materials for this paper because this portion is the only part of the present analysis that diverges from previously validated measures outlined in cited publications.

Appendix B2: *Open-Ended Interview Script for Proposed Second Experimental Design*

Appendix B2 shows the script that would be followed by the interviewer while conducting the interview portion of the second experimental design. Questions are divided into three sections: Gambling Task, ER40, and Life Experience. Each section includes five questions, and participants are not restricted in the time they take to respond to each. Upon conclusion of the interview, the interviewer asks participants to remain present and outlines the debriefing that will follow.

Note. The script for the interview portion is included in the materials for this paper because this portion is the only part of the present analysis that diverges from previously validated measures outlined in cited publications.

B1: INFORMED CONSENT

You may take as long as you need to review the following information. If you consent to take part in the following open-ended interview, information drawn from your responses may be used in a future publication. Participation in this interview is voluntary and can be withdrawn at any time. You will still be compensated for your participation in the behavioral paradigm if you do not complete the interview. If you participate in the interview, your answers will be audio-recorded. These files will be stored offline and deleted following transcription. Transcripts will also be stored offline. If you opt out of participation at any time after completion, any recordings or transcripts affiliated with your participation will be destroyed.

The following interview questions are included to contextualize the behavioral and neuroimaging results from the paradigm with narrative accounts of participants' experience. There are five questions related to the emotion recognition task, five questions related to the gambling task, and five questions related to lifestyle and behavior. No answers from any individual participant will be published. Words or phrases that appear in multiple participants' responses may be related to performance on behavioral measures. These will not be accompanied by any identifying information. Because portions of your responses may appear in the factor analysis included for publication, please refrain from providing any information you would not be comfortable seeing published.

Please check one of the boxes and sign your name on the line below:

☐ I understand and agree to participate in the interview portion of the paradigm.

☐ I understand and do not wish to participate in the interview portion.

X____

B2: OPEN-ENDED INTERVIEW SCRIPT

Participant #:
Age:
Gender:
Race/Ethnicity:

Open-ended questions:

ER40

Q1: How easy or difficult did you feel the emotion recognition task was?

Q2: Were there any specific faces that you recall struggling with more than others?

Q3: Were there any emotions more difficult to identify than others?

Q4: How do you believe your performance compares to that of others?

Q:5 Did you note any patterns in your performance beyond those listed above? If so, do you believe they related to any internal or external factors you noted?

GAMBLING TASK

Q6: Were there any points at which you struggled to make a decision on the gambling task?

Q7: How do you believe your performance compares to that of other participants?

Q8: How do you believe the time you took to respond compares to that of other participants?

Q9: Do you believe there were any patterns in your performance throughout the task? If so, do you believe they related to any internal or external factors you noted?

Q10: Do you believe there were any patterns in the time it took you to respond throughout the task? If so, do you believe they related to any internal or external factors you noted?

This concludes the questions concerned with today's experiment. Please answer the last five questions in terms of your daily life.

LIFE EXPERIENCE

Q1: How do you believe your ability to recognize emotions compares to your peers?

Q2: How does your answer to the previous question relate to your experience of empathy?

Q3: How do you believe your attitude towards risk-taking compares to your peers?

Q4: Do you enjoy gambling? If you feel comfortable, describe gambling behavior in your present life and whether your behavior has changed over time.

Q5: Do you believe your performance on the behavioral tasks relates to your experience in daily life? Describe the reasons for your answer. (Please respond separately for each task.)

This concludes the interview portion of the experiment. Thank you for your participation today. Please remain in the lab for a short debriefing. This debriefing will include contact information for the principal investigator. If you have additional questions about the experiment or wish to modify the consent you have provided today, please feel free to reach out using the email or phone number provided.