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Common neural dysfunction of economic decision-making across psychiatric conditions

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ABSTRACT

Adaptive decision-making, which is often impaired in various psychiatric conditions, is essential for well-being. Recent evidence has indicated that decision-making capacity in multiple tasks could be accounted for by latent dimensions, enlightening the question of whether there is a common disruption of brain networks in economic decision-making across psychiatric conditions. Here, we addressed the issue by combining activation/lesion network mapping analyses with a transdiagnostic brain imaging meta-analysis. Our findings indicate that there were transdiagnostic alterations in the thalamus and ventral striatum during the decision or outcome stage of decision-making. The identified regions represent key nodes in a large-scale network, which is composed of multiple heterogeneous brain regions and plays a causal role in motivational functioning. The findings suggest that disturbances in the network associated with emotion- and reward-related processing play a key role in dysfunctions of decision-making observed in various psychiatric conditions. This study provides the first meta-analytic evidence of common neural alterations linked to deficits in economic decision-making.

1. Introduction

Decision-making generally refers to making a choice guided by a comparison of the utility or subjective value of available options (Berridge and O'Doherty, 2014; Neumann and Morgenstern, 1972). Making appropriate choices is critical for securing the resources required for human survival and development. Maladaptive decisions, conversely, result in serious problems, such as poverty and homelessness, and are associated with many psychiatric disorders (Haushofer and Fehr, 2014; Sharman et al., 2016). For example, several psychiatric disorders, including conduct disorders (CD), substance use disorders (SUD), depression, schizophrenia, and gambling disorder (GD), often exhibit a diminished ability to make adaptive economic decisions (Baek et al., 2017; Fujino et al., 2018; Huang et al., 2016; Hulvershorn et al., 2015; Jin et al., 2022). These findings indicated that economic decision-making impairment is transdiagnostic and may constitute a core facet of various psychiatric disorders (Griffiths et al., 2014; Lee, 2013). Accordingly, it is imperative to reveal potential common neuropsychological deficits related to economic decision-making across psychiatric conditions.

Economic decision-making can be decomposed into at least two stages. First, in the decision stage, individuals need to evaluate and compare the subjective utility of alternatives for selection by integrating various information such as risk/probabilities (likely/unlikely), valence (gains/losses), and timing (immediate/delayed), resulting in a decision plan into action (Berridge and O'Doherty, 2014; Goschke, 2014; Rangel et al., 2008; Sonuga-Barke et al., 2016). Second, in the outcome stage, individuals would compare expected and derived utility, with the differences between them resulting in prediction errors. This stage recruits the processing of emotions related to feedback (e.g., gains) and the

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assignment of updated value to the next actions (Rangel et al., 2008; Schultz, 2015).

Each of the abovementioned stages engages the recruitment of multiple psychological components, such as reward processing and evaluation; notably, psychiatric disorders often exhibit consistent impairments in these functions (Feng et al., 2022; McTeague et al., 2017, 2020; Sha et al., 2019). For instance, heightened responsiveness to rewards or reduced responsiveness to losses is a characteristic feature of CD and SUD (Fairchild et al., 2009; Voon et al., 2015). As for depressed patients, they often display a heightened aversion to risk and loss (Baek et al., 2017) and they may have an impaired ability to process social fairness and reward, as evidenced by a lack of response in the nucleus accumbens and dorsal caudate (Gradin et al., 2015; He et al., 2019). Moreover, many mental illnesses are linked to exaggerated temporal discounting, such that those patients often favor smaller amounts of immediate reward over larger future rewards to a larger extent compared to healthy controls (Blair et al., 2020; Sonuga-Barke, 2014; White et al., 2014). In addition, patients with disruptive behavior disorders (DBD) and SUD have difficulty learning to avoid decks with high penalties, suggesting a challenge in adjusting behavior after negative reinforcement (Schutter et al., 2011). Overall, empirical indications suggest that psychiatric disorders are associated with various economic decision-making deficits, which likely result from dysfunctions in multiple psychological processes important for decision-making (Goschke, 2014; Rangel et al., 2008; Scholl and Klein-Flügge, 2018).

With the advances in neuroeconomics and social neuroscience, a large body of studies has examined the neuropsychological components underlying economic decision-making by combining neuroimaging techniques (e.g., functional MRI) with various economic games (Glimcher and Fehr, 2014). Overall, the brain regions associated with economic decision-making were embedded in several different but interconnected brain networks implicated in emotion/reward processing, value encoding, and cognitive control. These networks include key nodes in the salience network (SN) and the central executive network (CEN), such as the amygdala, thalamus, lateral prefrontal cortex (lPFC), ventral striatum (VS), orbitofrontal cortex (OFC), and anterior cingulate cortex (ACC) (Goschke, 2014; Miller and Cohen, 2001; Peters and Büchel, 2010; Preuschoff et al., 2006; Sonuga-Barke et al., 2016; Tobler et al., 2007; Tom et al., 2007; Wilson et al., 2018). Notably, there has been a huge interest in applying neuroeconomics to psychiatry, and an increasing body of evidence in this research field has revealed that dysfunctional affective and cognitive processes in psychiatric diseases are associated with abnormalities in those networks previously implicated in decision-making, leading to unreliable or adverse choice behaviors (Cai et al., 2022; Carlisi et al., 2017; Maresh et al., 2014; Robson et al., 2020; Wang et al., 2015; Yao and Kendrick, 2022). In short, prior research has made significant strides toward explaining the neuropsychological underpinnings of economic decision-making and the functional abnormalities across psychiatric disorders.

However, economic decision-making may not reflect a unified process due to the complexity of the experimental paradigms, varying cognitive demands, and their reliance on multiple processes (Brand et al., 2007; Endrass and Ullsperger, 2021; Groen et al., 2013). It remains challenging to describe how psychiatric conditions relate to difficulties in the specific cognitive processes of economic decision-making. Nevertheless, a recent study has revealed a central construct that captures general decision-making capacity, which was extracted from a task battery of various decision-making including reinforcement-learning, risk, Pavlovian heuristics, and uncertainty processing. Notably, the central construct is associated with resting-state networks and mental health metrics (Moutoussis et al., 2021). The central construct has notable test-retest reliability, which is higher than that of individual decision-making tasks (Enkavi et al., 2019; Moutoussis et al., 2021). These results imply that there exists covariation across decision-making behaviors, implying that decision-making capacity could be represented by latent dimensions that broadly capture the shared variance within the population. More importantly, this points towards a novel approach to examining common decision-making impairment—from viewing different decision-making behaviors as unique phenomena engaging distinct psychological processes to considering a general decision capacity strongly constrained by several core neuropsychological components transcending various decision behaviors. In this sense, a key question is enlightened: is there a common disrupted core region/network in psychiatric disorders that leads to their dysfunction in general economic decision-making capacity?

To shed light on this important question, we aimed to reveal transdiagnostic impairments in economic decision-making across various experimental paradigms by employing an integrative, transdiagnostic framework in this study. The transdiagnostic approach is appropriate due to the increasing focus on defining fundamental aspects of pathophysiologic dysfunction that transcend various clinical manifestations (Zald and Lahey, 2017). For instance, recent studies have revealed transdiagnostic deficits of cognitive control (McTeague et al., 2017), emotional processing (McTeague et al., 2020), and reward anticipation (Feng et al., 2022). Similarly, a common structural disturbance is evident across a variety of psychiatric disorders (Goodkind et al., 2015; Kempton et al., 2011; Li et al., 2020). Therefore, it seems reasonable to hypothesize that common neuropsychological systems might be implicated in potential patterns of impairment in economic decision-making across psychiatric diseases.

In particular, we implemented a transdiagnostic meta-analysis using coordinate-based activation likelihood estimation (ALE) to integrate brain imaging results from diverse economic decision-making tasks, aiming to examine functional impairment during economic decision-making vulnerable to broad-spectrum psychopathology. This method avoids the variability and divergence of earlier findings from small sample sizes by statistically analyzing convergence across studies, providing a comprehensive perspective on a research topic (Fox, 2018; Gurevitch et al., 2018). Notably, activation network mapping—a novel and validated technique that maps activation foci to brain networks rather than local regions—was added to the current transdiagnostic meta-analysis (Darby et al., 2018, 2019; Feng et al., 2022; Peng et al., 2022). Since complex symptoms are embedded in a large-scale brain network made up of heterogeneous regions, activation network mapping is an appropriate technique for examining their neurobiological foundation (Fox, 2018). Specifically, we examined the transdiagnostic patterns of brain regions/networks related to the decision stage and the outcome stage of decision-making behaviors, with the aim of revealing neural circuits underlying common impairment in general decision capacity across various psychiatric disorders. According to previous findings, we hypothesized that transdiagnostic dysfunction manifests in crucial nodes of large-scale networks that subserve emotion, reward, and cognitive processing.

2. Materials and methods

2.1. Literature search and selection

Systematic and comprehensive searches of the ISI Web of Science and PubMed databases were conducted in April 2023, following PRISMA procedures (Shamseer et al., 2015). The search terms were created by combining three types of relevant terms as follows: (1) imaging modalities: "fMRI" OR "magnetic resonance imaging" OR "PET" OR "positron emission tomography" OR "neuroimaging"; (2) economic decision-making: "delay discounting task" OR "Iowa Gambling Task" OR "Cambridge Risk Task" OR "Wheel of Fortune" OR "Lane Risk Taking Task" OR "Risky-Gains Decision-Making Task" OR "Two-choice card task" OR "Card-playing task" OR "Choice reversal task" OR "Two-choice prediction task" OR "Card decision task" OR "decision-making" OR "risk assessments" OR "risky choices" OR "gambling" OR "loss aversion" OR "uncertainty" OR "ambiguity" OR "probability" OR "prospect theory" OR "time preferences" OR "inter-temporal choice" OR "temporal

discounting" OR "revealed and real preferences" OR "substitution for pathogenetic goods" OR "expected utility function" OR "cost-benefit analysis" OR "exaggerated valuation of costs" OR "transferred money" OR "sensitivity to increasing gains and losses" OR "excessive present-orientation" OR "valued-based" OR "markov decision process" OR "model-based" OR "model-free"; and (3) disorder diagnosis: "schizophrenia" OR "schizophreniform" OR "SCZD" OR "psychosis" OR "psychotic disorders" OR "psychopathy" OR "psychopathic" OR "psychopath" OR "mentally disordered" OR "PCL-R" OR "Autism spectrum disorder" OR "ASD" OR "Asperger" OR "Asperger syndrome" OR "attention deficit hyperactivity disorder" OR "ADHD" OR "affective disorders" OR "bipolar disorder" OR "unipolar disorders" OR "mania" OR "manic disorder" OR "dissociative disorder" OR "dysthymia" OR "major depressive disorder" OR 'MDD' OR "depression" OR "disruptive mood regulation disorders" OR "dysthymia" OR "mood disorder" OR "generalized anxiety disorder" OR "GAD" OR "mood and anxiety disorders" OR "anxiety disorder" OR "panic disorder" OR "agoraphobia" OR "phobia" OR "obsessive--compulsive disorder" and "OCD" OR "post-traumatic stress disorder" OR "stress disorder" OR "PTSD" OR "post-traumatic stress" OR "eating disorders" OR "anorexia nervosa" OR "Bulimia nervosa" OR "binge and heavy drinking" OR "overweight" OR "obesity" OR "conduct disorder" OR "conduct problems" OR "disruptive behavior disorder" OR "oppositional defiant disorder" OR "intermittent explosive disorder" OR "callous unemotional" OR "disruptive behavior" OR "defiant behavior" OR "externalizing" OR "intermittent explosive" OR "substance abuse" OR "substance use disorder" OR "SUD" OR "cannabis" OR "marijuana" OR "marihuana" OR "THC" OR "tetrahydrocannabinol" OR "cigarette--smoking" OR "nicotine" OR "Alcohol misuse" OR "Alcohol abuse" OR "Alcohol addiction" OR "heavy drinking" OR "binge drinking" OR "alcohol dependence" OR "Internet gaming disorder" OR "Internet addiction" OR "IGD" OR "antisocial personality disorder" OR "antisocial behavior" OR "antisocial" OR "borderline personality disorder" OR "BPD". The large number of keywords employed in the current study was to ensure a comprehensive search of related studies. Additionally, we investigated various other sources, such as (1) the BrainMap database (http://brainmap.org), (2) the bibliographies and citation indices of the previously selected papers, and (3) the reference lists of relevant reviews (e.g., Hauser et al., 2014; Lee, 2013; Robson et al., 2020), and (4) direct queries using the names of authors who appear regularly.

The identified studies were further evaluated using the subsequent criteria. First, the study was published in a peer-reviewed English language journal and presented empirical data. Second, subjects performed an economic decision-making task. Third, each study referred to at least one psychiatric disorder or at-risk population (e.g., relatives of psychiatric disorder or individuals with psychotic characteristics) versus control group comparisons on the decision or the outcome phases. During the decision phase, participants processed the experimental stimulus and pressed the keys to respond. During the outcome phase, participants were presented with the results of the current trial (i.e., feedback). Fourth, we limited the meta-analysis to research employing fMRI or PET, as well as research that presented whole-brain functional neuroimaging data instead of ROI analyses. Fifth, a general linear model based on parametric analyses or binary contrasts was used to produce the results. Sixth, a standardized stereotaxic space (Talairach or Montreal Neurological Institute, MNI) was used to display activations. It should be noted that for publications using Talairach coordinates, the icbm2tal algorithm has been used for conversion into MNI coordinates (Lancaster et al., 2010). Lastly, participants did not have a history of neurological diseases (e.g., epilepsy, brain tumor, brain lesion, or meningitis). After applying these inclusion/exclusion criteria to search results, a total of 136 experiments (i.e., contrasts) from 67 published fMRI publications were found (Fig. 1).

2.2. Activation likelihood estimation (ALE) approach

Using the ALE algorithm, a coordinate-based meta-analysis of published fMRI investigations was performed (Eickhoff et al., 2017; Eickhoff et al., 2009). ALE assesses the convergence of published foci in Talairach or MNI space (Laird et al., 2005; Turkeltaub et al., 2002). According to ALE, reported foci are to be regarded as spatial probability distributions whose widths are experimentally approximated to account for the spatial uncertainty arising from the variation in neuroimaging data across participants and templates (Eickhoff et al., 2009). For each voxel included in every experiment, a modulated activation (MA) map is generated using the highest likelihood connected to any focus, which is inevitably the closest one (Turkeltaub et al., 2012). The updated ALE method has the benefit of avoiding the joint influence of several foci from a single experiment on the individual MA value of a particular

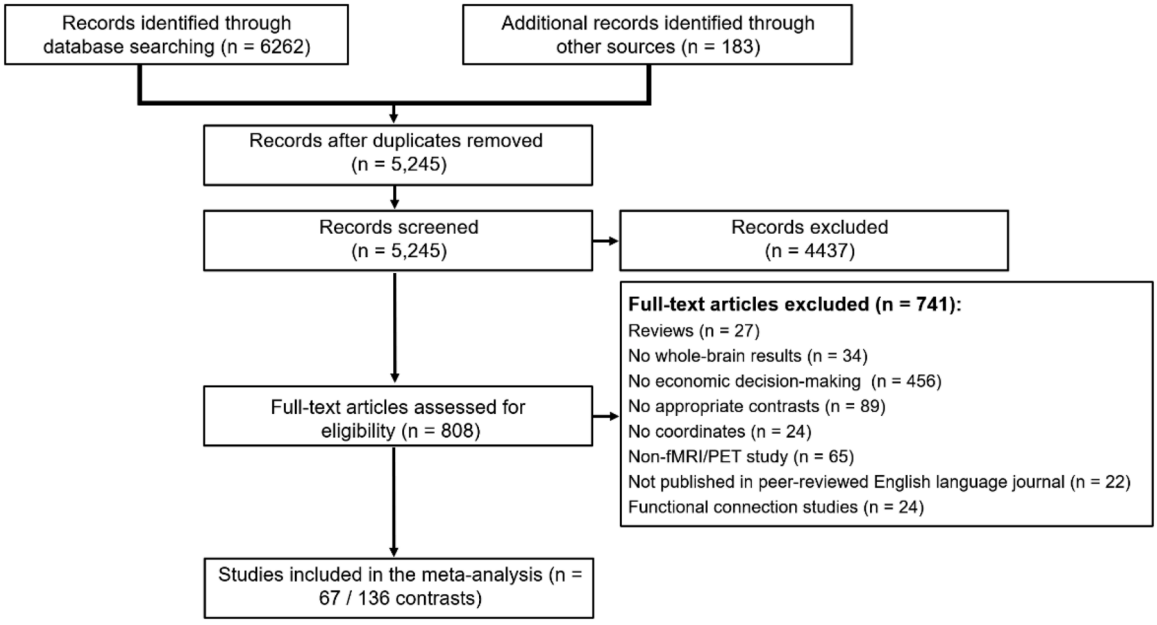

Fig. 1. Diagram representing the flow of the meta-analysis's study selection procedure. fMRI, functional magnetic resonance imaging; PET, positron emission tomography.

voxel. To generate an ALE map across experiments, the individual MA maps are combined using the highest likelihood related to any one focus for each voxel. Applying a non-linear histogram integration approach, this ALE map is evaluated against a null distribution of random spatial associations among experiments (Eickhoff et al., 2012; Turkeltaub et al., 2012). Moreover, the contribution of each experiment was computed as the fraction of the ALE value accounted for by the given experiment contributing to the cluster (Eickhoff et al., 2016). To select significant clusters, we applied two more criteria based on the computed contribution. To ensure that no single experiment dominates a cluster, each cluster must obtain contributions from at minimum two experiments. Additionally, neither the mean contribution of the most dominant experiment (MDE) nor the mean contribution of the two most dominant experiments (2MDEs) ought to surpass 50% or 80% (Eickhoff et al., 2016).

The published coordinates of brain regions linked to variations in economic decision-making between psychiatric conditions and healthy controls converged across various experiments employing the ALE algorithm. Particularly, these meta-analytic techniques were used to converge the neural correlates of aberrant economic decision-making across psychiatric conditions (136 contrasts in total): (i) altered brain activity in psychiatric conditions compared to controls during decision phase (psychiatric conditions > controls or controls > psychiatric conditions: 93 contrasts, 555 foci) (for a similar approach see McTeague et al., 2017); and (ii) altered brain activity in psychiatric conditions compared to controls during outcome phase (psychiatric conditions > controls or controls > psychiatric conditions: 43 contrasts, 169 foci). We additionally conducted alternative analyses that only included clinical populations for both the decision (82 contrasts, 458 foci) and outcome (38 contrasts, 117 foci) phases in order to prove the reliability of the present findings. The results of the complementary analyses were illustrated in the supplementary material (see also supplementary results for details).

2.3. Functional decoding for identified regions

Functional decoding analyses were conducted based on the Neurosynth database (version 0.6) (Yarkoni et al., 2011) by utilizing codes from a series of IPython Notebooks (https://github.com/adelavega/neurosynth-lfc) to investigate which psychological topics were most pertinent to brain areas associated with differences between psychiatric conditions and healthy controls in economic decision-making converged across different experiments (de la Vega et al., 2018). With 11,406 publications covering all angles of the reported neuroimaging papers, Neurosynth is a platform for large-scale fMRI meta-analysis (Yarkoni et al., 2011). The peak coordinates for every activation and frequency of words in the abstract of each fMRI study are stored in the Neurosynth database. Latent Dirichlet allocation topic modeling was utilized to identify psychological topics, which led to the discovery of 60 distinct topics on the basis of the co-occurrence of each term in the abstracts (de la Vega et al., 2018). Initially, we created six brain masks composed of areas found during the decision and outcome phases (three masks for the main results of psychiatric conditions and three masks for the supplementary results of clinical populations). Two sets of studies were subsequently chosen for each brain mask: those that failed to activate any voxels (inactive research) and those that activated at minimum 5% of the voxels within the mask (active research). Then, based on the loading of each psychological topic onto individual research, a naive Bayes classifier was trained to distinguish between these two sets of studies. The log of the ratio between the likelihood of each topic in inactive research and the likelihood of that topic in active research was employed to generate 60 log odds-ratio (LOR) values for each brain mask. After identifying the semantic content of the research, a LOR value above zero suggested that the related psychological theme was forecasting whether a study activated areas in a specific brain mask. Lastly, the significance level of the observed LOR values was ascertained using a permutation-based technique that involved rearranging research labels (i.e., active or inactive) 1000 times. Please note that the provided topics were limited to those that produced significant findings ($p < 0.01$) in false discovery rate (FDR) multiple comparisons.

2.4. Lesion network analysis

The lesion network analysis involves mapping lesion-induced symptoms to brain networks rather than local regions. This is achieved by combining lesion locations with maps of resting-state functional connectivity (RSFC) derived from normal, nonsymptomatic populations (Boes et al., 2015; Darby et al., 2017). Specifically, the lesion network mapping process comprises the subsequent steps: (i) duplicating the volume of each lesion onto a reference brain; (ii) employing RSFC to assess the network of brain regions functionally linked to each lesion location; and (iii) revealing the overlap of networks connected to each lesion location as common network sites. A lesion network was identified for motivation-related symptoms in our earlier study (Feng et al., 2022). Within this network, the ventral striatum stands out as the central node, encompassing diverse lesion locations that result in functional abnormalities related to motivation, such as apathy and anhedonia. The current study further explored whether brain networks causally connected to motivational impairments coincide with brain regions arising from decision-making deficiencies across neuropsychiatric disorders, given the crucial role of motivation-related processes in decision-making.

2.5. Activation network mapping

Activation network mapping was performed to examine whether brain activations from different experiments were restricted to the same network. This innovative method combines maps of RSFC with reported activation foci to map psychological constructs to brain networks instead of local regions. In our case, the activation network mapping can provide complementary evidence for the meta-analysis by providing information about the brain network rather than localized brain regions, helping to understand the potential connectivity among the heterogeneous brain regions (Peng et al., 2022). Such a network approach is particularly relevant to identifying neurobiological systems underlying human decision-making deficits as a complex and multidimensional construct. Indeed, rather than focusing on particular brain regions, there is growing recognition that human decision-making is best described in terms of interactions across large-scale brain networks consisting of dispersed brain locations (Feng et al., 2021).

2.5.1. Participants

The activation network mapping was performed on resting-state functional magnetic resonance imaging (rs-fMRI) images of 116 healthy adult volunteers (57 males; 21.80 ± 2.41 years old; age range 18–30; Beijing Normal University, China). Participants were instructed to close their eyes, remain still, and stay attentive without concentrating on any specific ideas during the rs-fMRI scan. Approved by the local Ethics Committee, the rs-fMRI study was performed in compliance with the Declaration of Helsinki. All participants provided written informed consent. They were all right-handed and had no history of neurological or mental illness.

2.5.2. Resting-state fMRI data acquisition

At the Beijing Normal University Imaging Center for Brain Research, functional images of the subjects in the resting state were collected using a Siemens TRIO 3 Tesla scanner. The rs-fMRI scan comprised 150 contiguous volumes obtained through an echo-planar imaging sequence (axial slices, 33; slice thickness, 3.5 mm; interslice gap, 0.7 mm; TR, 2000 ms; TE, 30 ms; flip angle, 90°; voxel size, 3.5 × 3.5 × 3.5 mm^3; FOV, 244 × 244 mm^2). Moreover, a 3D sagittal T1-weighted magnetization-prepared rapid acquisition with gradient-echo sequence was

employed to capture high-resolution structural images (sagittal slices, 144; TR, 2530 ms; TE, 3.39 ms; slice thickness, 1.33 mm; voxel size, 1 × 1 × 1.33 mm^3; flip angle, 7°; inversion time, 1100 ms; FOV, 256 × 256 mm^2).

2.5.3. Resting-state fMRI data analysis

The DPABI was used for neuroimaging data analyses (Yan et al., 2016). As a consequence of participant adjustment to the scanning noise and signal equilibrium, the first 10 vol of the functional pictures were removed for signal equilibrium. Images were then realigned to account for head movement. Sixteen participants (8 males) were eliminated from data analyses due to head movements beyond the limit of translation of 1.5 mm, rotation of 1.5°, and average frame-wise displacement of 0.2 mm throughout the scanning process (Power et al., 2012; Yan et al., 2013). The structural brain images of the participants were first co-registered to their own mean functional images, and then they were segmented to normalize the functional images. Each participant's functional images were normalized into the standard Montreal Neurological Institute space (MNI template, resampling voxel size was 2 × 2 × 2 mm^3) using the segmentation parameters. Subsequently, the time courses' linear trends were eliminated, and each voxel's time series underwent band-pass filtering (0.01–0.1 Hz) to lessen the impact of high-frequency physiological noise and low-frequency drift (Biswal et al., 1995; Zuo et al., 2010). Then, four nuisance variables were regressed out: (i) the global mean signal, (ii) the white matter (WM) signal, (iii) the cerebrospinal fluid signal (Fox et al., 2005; Snyder and Raichle, 2012), and (iv) 24 movement regressors, which included autoregressive models of motion comprising 6 head motion parameters, 6 head motion parameters one time point prior, and the 12 corresponding squared items (Friston et al., 1996). Time points with excessive motion were then censored to remove residual motion artifacts (Power et al., 2012). Lastly, an additional head motion control was applied. This resulted in volumes with an FD > 0.5 mm, as well as the volume before it and the two volumes after it, being categorized as micromovement-containing volumes. These volumes were then modeled as individual regressors in a nuisance covariate regression (Power et al., 2014; Yan et al., 2013).

2.5.4. Activation network mapping analysis

The activation network mapping involved the following steps (Peng et al., 2022): (i) For each experiment included in a given analysis (i.e., decision phase, outcome phase, or both phases), 6-mm-radius spheres centered on all reported foci/coordinates were created and then merged within the experiment to produce a single "activation seed". (ii) We defined activation network maps as brain regions functionally linked to the activation seed by applying seed-based RSFC on the resting-fMRI data. Specifically, the Pearson's correlation coefficient between the mean BOLD signals from the activation seed and the rest of the brain voxels was determined for each participant. (iii) Fisher *z* maps were generated from Pearson's correlation coefficients acquired at each voxel to demonstrate the level of connection between each ROI and voxel. (iv) A mean Fisher *z* map was produced for each experiment by averaging the Fisher *z* maps of all 100 subjects. (v) One-sample *t*-tests were employed to compare these mean maps of all experiments with zero. The *t*-tests were thresholded at a voxel-level Family-Wise Error (FWE) correction of $p < .05$ and required a minimum cluster volume of 20 voxels unless specified otherwise. Then activation network t maps were obtained and the resulting clusters represented brain regions that exhibited significant connectivity to the activation seeds across multiple experiments.

2.6. Leave-one-experiment-out (LOEO) analysis

Additional analyses were implemented to validate the results of the conventional ALE meta-analysis approach. For every ALE meta-analysis, an LOEO analysis was conducted to ensure the conclusions drawn from the primary meta-analysis were not influenced by the coordinates from a single experiment. One experiment from each fold was eliminated and the rest of the N-1 experiments were subjected to the ALE meta-analysis. Aiming to determine the brain regions substantially engaged, we performed conjunction analysis on the ALE results for each fold. In the LOEO study, the indicated brain regions were identified in more than 80% of the folds. We employed these analyses to corroborate the primary results of the ALE meta-analysis.

3. Results

3.1. Studies included in meta-analyses

A total of 68 PET/fMRI studies (136 experiments) were included in the present meta-analyses. Specifically, the present meta-analysis included the following set of clinical/at-risk populations: (1) addiction-related populations, consisting of patients with alcohol dependence, binge eating disorder, cocaine-dependence, pathological gambling, obesity, marijuana users, and smokers (70 experiments); (2) mood/anxiety-related populations, consisting of patients with obsessive compulsive disorder, anxiety disorders, major depressive disorder, bipolar disorder, and people with rumination symptoms and early life stress (19 experiments); (3) behavior-related populations, including patients with borderline personality, attention deficit hyperactivity disorder, external disorder (mainly oppositional defiant disorder), autism spectrum disorder, and people vulnerable to antisocial behavior (38 experiments); and (4) psychosis-related populations, including schizophrenia patients and people with subclinical psychotic experiences and risk to develop psychosis (9 experiments). Moreover, the present meta-analysis comprised the following experimental paradigms: (1) delay discounting task (26 experiments); (2) risk-related task (93 experiments), including balloon analog risk task, cup task, Iowa gambling task, card gambling task, financial decision-making task, Rogers decision- making task, wheel of fortune task, win-and-losses task and other similar risk-related tasks; (3) passive avoidance task (10 experiments); (4) effort-expenditure for rewards task (5 experiments); and (5) tasks associated with sunk costs (2 experiments).

3.2. Main ALE meta-analyses results

For the decision phase, examining the contrasts of aberrant activation (i.e., pooling across patterns of hyper- and hypo-activation) in psychiatric conditions compared to controls revealed consistent maxima in the right ventral striatum (VS) (TFCE, corrected of $p < 0.05$, Fig. 2A & Table 1). Cluster 1 was derived from ten of the ninety-three contrasts (MDE = 39.58%; 2MDE = 75.51%) and cluster 2 was derived from fifteen of the ninety-three contrasts (MDE = 12.84%, 2MDE = 22.55%) in the right VS. According to the functional decoding analysis, the obtained cluster was primarily linked to food, sequences, reward, decision-making, and learning processes (Fig. 3A). Regarding the outcome phase, consistent maxima were revealed in right VS and bilateral subgenual anterior cingulate cortex (sgACC) (TFCE, corrected of $p < 0.05$, Fig. 2B & Table 1). The cluster in the right sgACC was derived from seven out of forty-three contrasts (MDE = 26.66%; 2MDE = 50.10%), whereas the cluster in the left sgACC was derived from six out of forty-three contrasts (MDE = 36.42%, 2MDE = 69.05%). The cluster in the right VS was derived from five of the forty-three contrasts (MDE = 33.92%, 2MDE = 66.51%). The identified clusters were related to the functions of food, reward, fear, game, taste, smoking, learning, and decision-making processes revealed by the functional decoding analysis (Fig. 3B). As for contrasts in both decision and outcome phases, consistent maxima were revealed in right VS, right ventrolateral prefrontal cortex (vlPFC), right thalamus, and bilateral dorsal anterior cingulate cortex (dACC) (TFCE, corrected of $p < 0.05$, Fig. 2C & Table 1). The cluster in the right VS was derived from twenty-seven out of 136 contrasts (MDE = 9.18%, 2MDE = 17.74%). The cluster in the right vlPFC was derived from thirteen out of

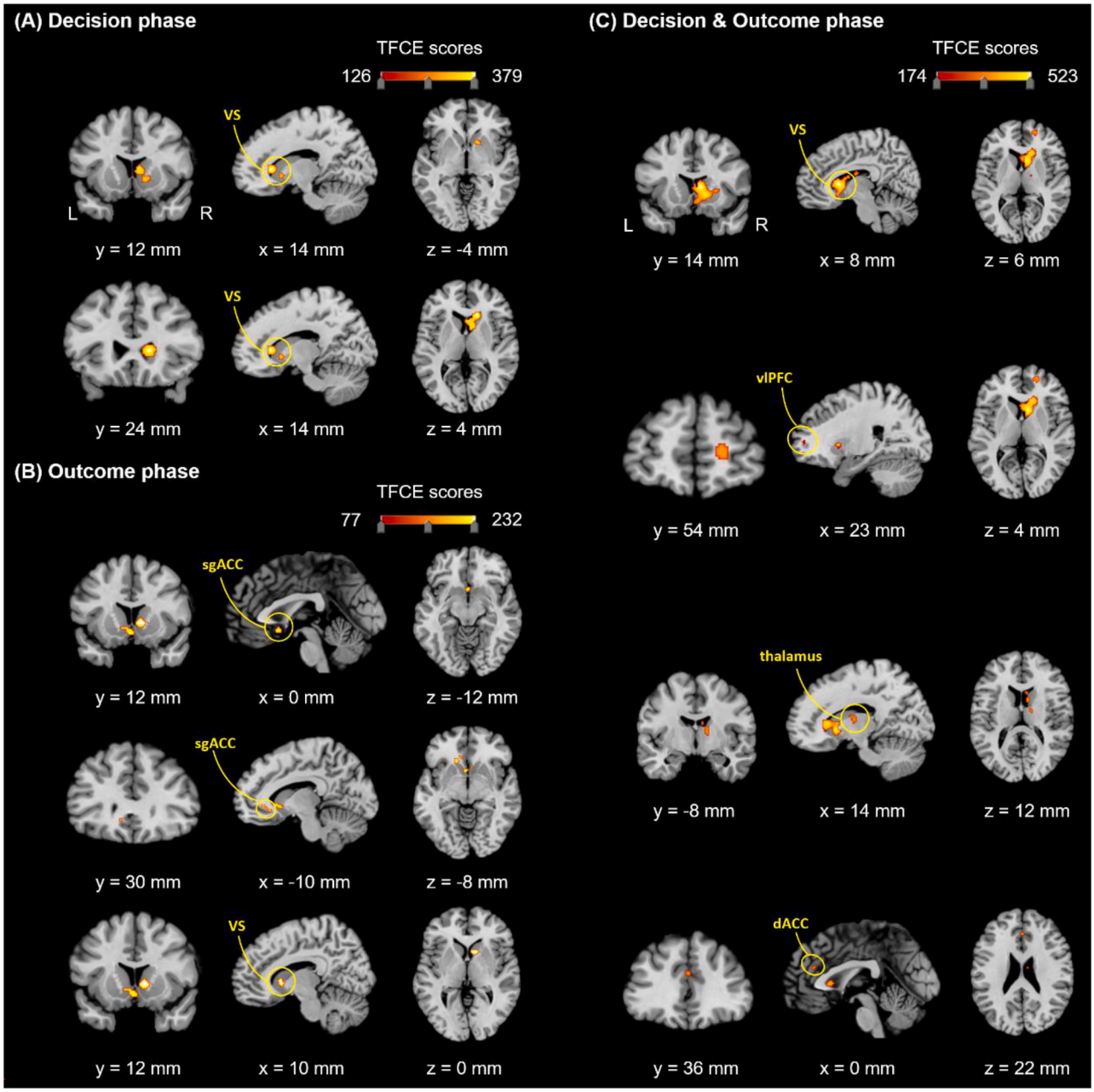

Fig. 2. Significant clusters from the meta-analysis in fMRI/PET studies of (A) the decision-making phase, (B) the outcome phase, and (C) both decision-making and outcome phases (aberrant activation in clinical/at-risk conditions relative to controls). The significant clusters were found using Threshold-Free Cluster Enhancement (TFCE) at $p < 0.05$. L, left; R, right; VS, ventral striatum; vlPFC, ventrolateral prefrontal cortex; dACC, dorsal anterior cingulate cortex; sgACC, subgenual anterior cingulate cortex.

136 contrasts (MDE = 23.56%, 2MDE = 45.74%). The cluster in the right thalamus was derived from thirteen out of 136 contrasts (MDE = 37.86%, 2MDE = 72.68%). The cluster in the bilateral dACC was derived from eight out of 136 contrasts (MDE = 31.24%, 2MDE = 61.06%). The identified clusters were related to food, sequences, reward, pain, fear, decision-making, and learning processes, according to the functional decoding analysis (Fig. 3C). Notably, the results of the LOEO approach corroborated the main findings of main ALE meta-analysis (see Fig. S4-S5 & Supplementary Results for details).

3.3. Conjunctions with lesion brain network

The conjunction analysis revealed overlaps in right VS between the lesion brain network causing motivation-related symptoms and the brain regions identified with the aberrant activation of the decision phase (Fig. 4A & Table 2). Similarly, in the outcome phase, right VS was also found in the conjunction analysis (Fig. 4B & Table 2). Furthermore, when considering both decision and outcome processes, overlaps in the right VS and thalamus were found (Fig. 4C & Table 2).

3.4. Results of activation network mapping

The ANM revealed brain systems commonly engaged by different phases. For the decision phase, the activation network mapping analysis revealed the right dorsal anterior cortex, bilateral striatum extending to the insula, and bilateral extra-nuclear extending to striatum (p (FWE) < 0.05 at the voxel level, Fig. 5A & Table 3). For the outcome phase, the right sgACC, right striatum extending to the insula and amygdala, and

Table 1
Significant clusters from the meta-analysis of individual differences in fMRI studies (aberrant activation in clinical/at-risk conditions relative to controls).

Laterality	Brain Regions	BA	MNI Coordinates (mm)			TFCE Score	Cluster Size (mm^3)
			x	y	z		
Group differences in decision phase (hyper-activation/hypo-activation)							
R	ventral striatum	–	14	12	−4	367.107	184
R	ventral striatum	–	14	24	4	505.338	1648
Group differences in outcome phase (hyper-activation/hypo-activation)							
L/R	subgenual anterior cingulate cortex	25	0	12	−12	298.611	392
L	subgenual anterior cingulate cortex	24	−10	30	−8	293.53	120
R	ventral striatum	–	10	12	0	309.408	320
Group differences in both decision and outcome phases (hyper-activation/hypo-activation)							
R	ventral striatum	–	8	14	6	697.312	4272
R	ventrolateral prefrontal cortex	10	20	54	4	410.583	280
R	thalamus	–	14	−8	12	367.754	144
R/L	dorsal anterior cingulate cortex	32	0	36	22	360.266	48

The significant clusters were found using Threshold-Free Cluster Enhancement (TFCE) at $p < 0.05$. L, left; R, right.

left insula were identified (p (FWE) < 0.05 at the cluster level, with the cluster-defining threshold of $p < 0.0001$ (uncorrected), Fig. 5B & Table 3). Moreover, when considering both the decision and outcome processes together, the activation network mapping analysis revealed bilateral striatum extending to the dorsal anterior cortex and insula and right extra-nuclear extending to striatum (p (FWE) < 0.05 at the voxel level, Fig. 5C & Table 3). Consequently, the activation network mapping results were consistent with the findings of the ALE meta-analysis.

4. Discussion

Making appropriate decisions plays a key role in human life, but the capacity is often impaired in many psychiatric disorders. The present meta-analysis aimed to uncover the common alterations in the neurobiological processes underlying various economic decision-making tasks across psychiatric conditions, leveraging extensive brain imaging studies that employ a range of economic experimental paradigms among diverse clinical/at-risk populations. We found a transdiagnostic pattern of functional alterations in the VS, sgACC, dACC, vlPFC, and thalamus, which are key nodes of a large-scale network typically associated with reward and emotional processing. Specifically, there is aberrant activation in the VS during the decisions phase as well as aberrant activation in the VS and sgACC during the outcomes phase across psychiatric conditions. Moreover, alterations in the VS, dACC, vlPFC, and thalamus activity were found among psychiatric conditions compared with healthy controls across both decision and outcome stages. Furthermore, we identified correspondence in the VS between brain networks implicated in motivational deficits and the brain regions associated with decision-making deficits present in diverse neuropsychiatric conditions. Lastly, our findings were further corroborated by the activation network mapping analysis, which demonstrated that activation foci associated with decision-making deficits across neuropsychiatric conditions are components of a distributed brain network with the VS, sgACC, dACC, and insula as key nodes. Collectively, dysfunction in a general economic decision-making capacity across psychiatry conditions may be rooted in disruptions of the "common core" of emotion- and reward-related processing.

The present results support Zald and Lahey's (2017) hierarchical model of psychopathology. According to the model, there are four levels in an ordered structure that comprise psychopathological symptoms: individual symptoms, first-order dimensions that resemble traditional diagnoses, broader second-order factors that include internalizing vs. externalizing, and a general psychopathology factor, also known as the *p*-factor. (Lahey et al., 2017; Zald and Lahey, 2017). Thus, shared alterations in the activity of key nodes in emotion- and reward-related networks may indicate higher-order dimension neuropsychological markers that transcend specific diagnoses (Husain and Roiser, 2018; Knutson and Heinz, 2015; Zald and Lahey, 2017). In accordance with this conjecture, recent behavioral evidence has suggested decision-making capacity in multiple choice tasks is supported by a similar cognitive construct (Moutoussis et al., 2021), which accounts for the individual differences in psychiatric conditions, such as abnormal cognitive processes and inadequate social function (Moutoussis et al., 2021). Our findings extend this behavioral evidence by revealing transdiagnostic alterations in emotion- and reward-related processing across a variety of decision-making tasks. In short, this work provides the first transdiagnostic meta-analytic evidence of how complex behavioral processes are compromised in psychiatric conditions.

Specifically, the current findings identified common neural dysfunction in areas related to emotional and reward processing across psychiatric conditions in economic decision-making. The identified areas, consisting of the ACC, thalamus, and VS, are critical for determining whether external stimuli are salient or relevant from a motivational perspective (William et al., 2007). The emotional and motivational signals encoded in these regions are important in regulating human decision-making across diverse contexts (Gu et al., 2019; Levy and Glimcher, 2012; Rangel et al., 2008), such that dysfunction in

Fig. 3. Functional decoding for clusters identified by meta-analyses of group differences at decision phase (A), outcome phase (B), or both (C).

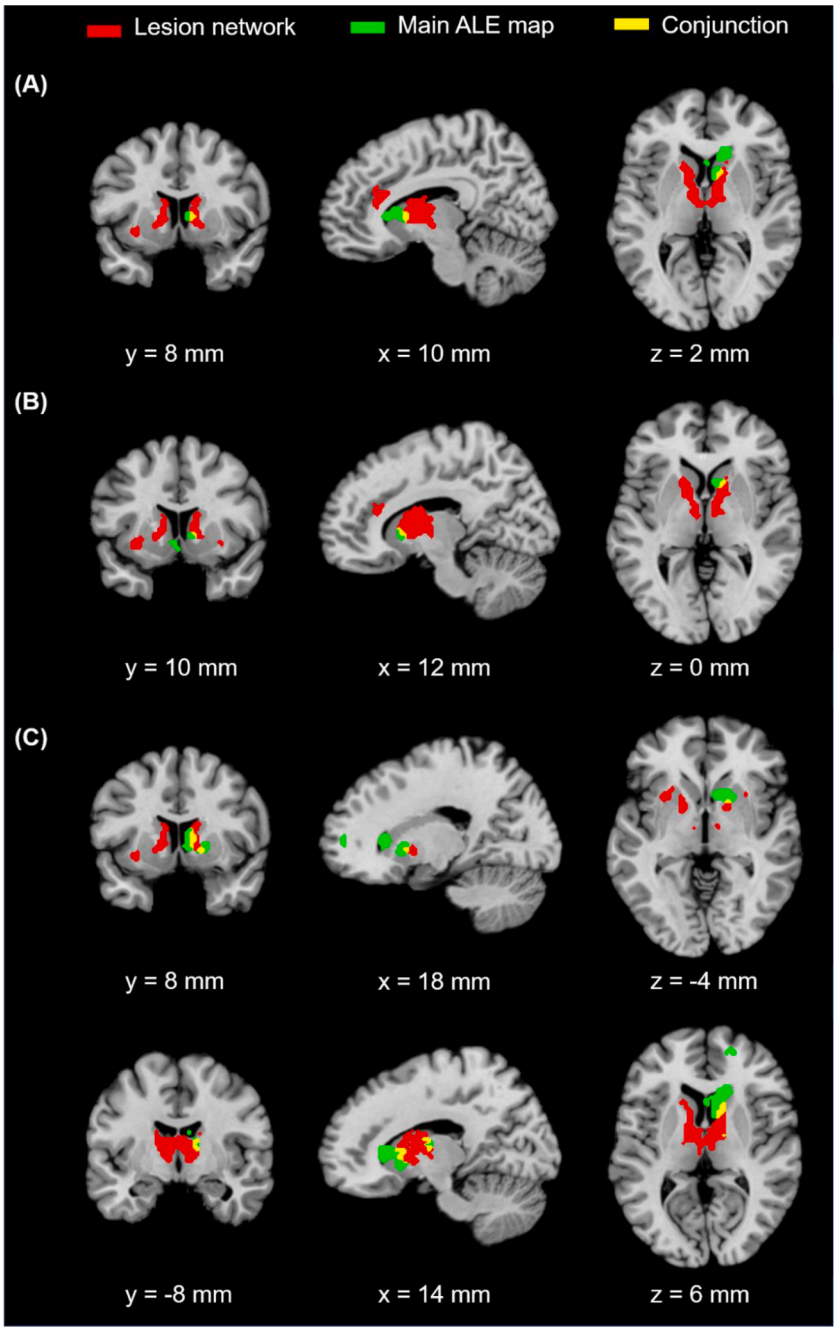

Fig. 4. Brain regions derived from the conjunction analysis with lesion network causing motivation-related symptoms. (A) Overlaps identified for the aberrant activation of the decision phase. (B) Overlaps identified for the aberrant activation of the outcome phase. (C) Overlaps identified for the aberrant activation of both decision and outcome phases.

these regions often results in decision-making deficits commonly present in psychiatric conditions (Lee, 2013; Robson et al., 2020). Consistent with the present results, prior research has recognized common structural and functional disruptions in salience network nodes across various psychiatric conditions (Feng et al., 2022; Goodkind et al., 2015; Li et al., 2020; McTeague et al., 2020). For example, there are transdiagnostic alterations in the VS while anticipating both reward and loss (Feng et al., 2022). Similarly, McTeague et al. (2020) identified common disruptions of the amygdala, thalamus, and vlPFC in emotional processing tasks. However, the present research is the first to demonstrate disruptions of emotion-related processes in human economic decision-making across psychiatric conditions.

Our meta-analytic findings were further complemented by the results of activation and lesion network mapping analyses, both of which map psychological constructs to large-scale networks instead of isolated brain regions. In particular, these analyses indicated that the identified regions (e.g., VS) represent key nodes in a large-scale network composed of numerous heterogeneous brain regions, which show common disruptions across psychiatric conditions and play a causal role in motivational functioning. These findings echo the assertion holding that the transdiagnostic functional construct or higher-order psychopathology factors are embedded in large-scale network disruptions as opposed to localized dysfunctions in specific nodes (Buckholtz and Meyer-Lindenberg, 2012; Zald and Lahey, 2017). In short, the pathophysiology of decision-making impairments (e.g., impulsivity and anhedonia) across categories of mental illness may be explained by a

Table 2
Brain regions derived from the conjunction with lesion network cause motivation-related symptoms.

Laterality	Brain Regions	BA	MNI Coordinates (mm)			Cluster Size (mm^3)
			x	y	z	
conjunction between group differences in decision phase and lesion results						
R	ventral striatum	–	10	8	2	120
conjunction between group differences in outcome phase and lesion results						
R	ventral striatum	–	12	10	0	72
conjunction between group differences in decision/outcome phase and lesion results						
R	ventral striatum	–	18	8	−4	488
R	thalamus	–	14	−8	6	104

L, left; R, right.

brain phenotype that underlies common disruptions in a large-scale network associated with emotion and reward processing, which encompasses various regions of the brain that collaborate to promote decision-making.

It is important to acknowledge that this study has certain limitations. First, the current study did not include brain imaging studies on social decision-making, given the limited number of studies available. Undoubtedly, social decision-making impairments play a significant role in the comprehension of psychopathology (Báez-Mendoza et al., 2021), hence, this topic should be saved for further research; for example, exploring whether there is common or differential brain dysfunction between economic and social decision-making across psychiatric conditions. Second, the insufficient number of studies for each psychiatric condition/task paradigm prevented the potential for investigating brain alterations specific to a diagnosis/task (Barch, 2020; Fusar-Poli, 2019), yet future meta-analyses will have greater statistical power to examine both common and unique abnormalities because the literature on the applications of economic games in psychiatry is expanding at a rapid pace. Third, further research on intervention studies is needed to determine if the transdiagnostic alterations in brain function represent the cause or consequence of psychopathology.

Regardless of these limitations, our study provides the first meta-analytic evidence of the common functional disruptions of emotion- and reward-related networks in economic decision-making across multiple clinical/at-risk populations. These findings suggest that emotion- and reward-related processing represent key neuropsychological processes that are important for decision-making, and their dysfunctions give rise to deficits in a general decision-making capacity. In other words, a general decision-making capacity may be strongly constrained by a few core neuropsychological components such as emotional processing and valuation. Our findings thus provide possible candidate brain phenotypes for future intervention studies, which may prove broad use across types of psychopathology.

Ethics statement

Informed consent and institutional ethical review committees are not applicable to this study.

CRediT authorship contribution statement

Chunliang Feng: Writing – review & editing, Supervision, Methodology, Conceptualization. **Qingxia Liu:** Writing – original draft,

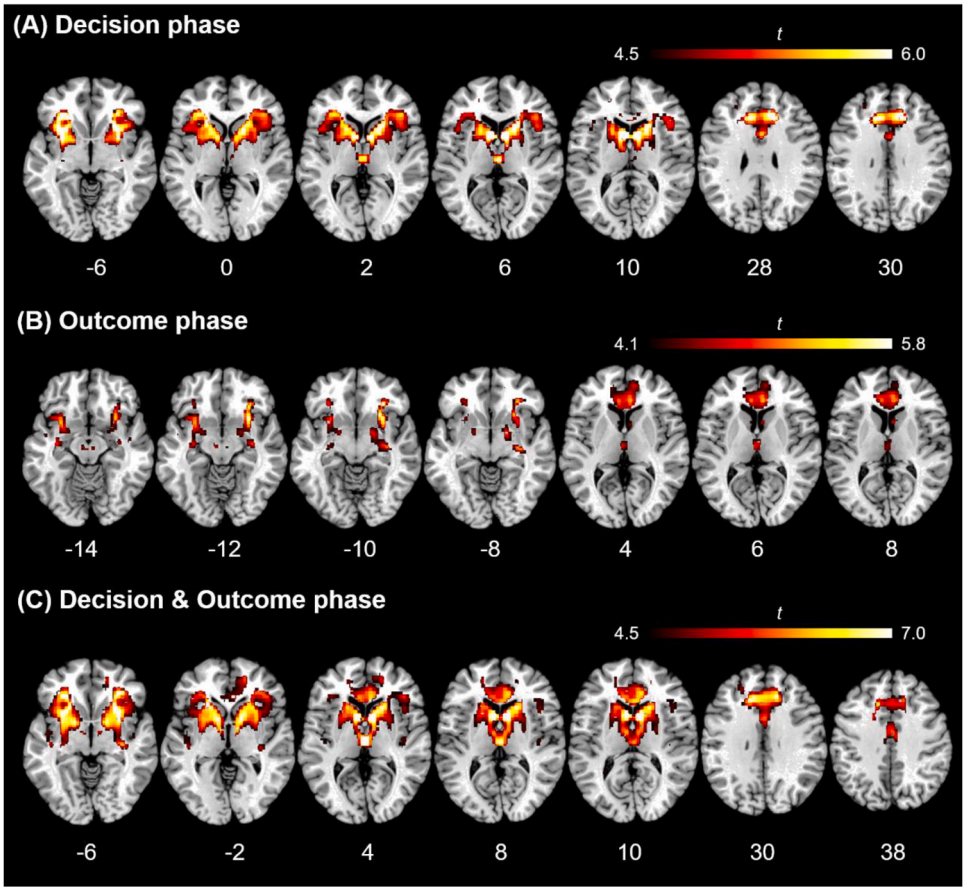

Fig. 5. Significant clusters from the activation network mapping (aberrant activation in clinical/at-risk populations relative to controls) of (A) decision-making phase (p (FWE) < 0.05 at the voxel level), (B) outcome phase (p (FWE) < 0.05 at the cluster level, with cluster-defining threshold of p (uncorrected) < 0.0001), and (C) both decision-making and outcome phases (p (FWE) < 0.05 at the voxel level).

Table 3
Significant clusters from the activation network mapping (aberrant activation in clinical/at-risk conditions relative to controls).

Laterality	Brain Regions	BA	MNI Coordinates (mm)			Peak intensity	Cluster Size (mm^3)
			x	y	z		
Activation network of the seed of decision phase							
L/R	striatum extending to insula	–	−4	10	10	7.972	45,792
R	dorsal anterior cingulate cortex	24	2	14	22	6.739	16,432
L	extra-nuclear extending to striatum	–	−20	−36	20	6.643	1088
R	extra-nuclear extending to striatum	–	24	−36	20	7.245	776
Activation network of the seed of outcome phase							
R	subgenual anterior cingulate cortex	24	8	34	6	5.199	14,120
R	striatum extending to insula and amygdala	–	28	16	−10	5.81	5528
L	insula	–	−28	10	−12	5.307	3384
Activation network of the seed of decision/outcome phase							
L/R	striatum extending to dorsal anterior cingulate cortex and insula	–	−6	10	8	8.595	103,856
R	extra-nuclear extending to striatum	–	22	−36	22	8.572	1272

Thresholds: decision phase and both decision-making and outcome phases: p (FWE) < 0.05 at the voxel level, outcome phase: p (FWE) < 0.05 at the cluster level, with cluster-definning threshold of p (uncorrected) < 0.0001. L, left; R, right.

Visualization, Validation, Software, Data curation. **Chuangbing Huang:** Software, Data curation. **Ting Li:** Writing – original draft, Data curation. **Li Wang:** Software. **Feilong Liu:** Data curation. **Simon B. Eickhoff:** Writing – review & editing. **Chen Qu:** Supervision, Conceptualization.

Declaration of competing interest

The authors are unaware of any conflicts of interest, financial or otherwise.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.neuroimage.2024.120641.

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