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Letter to the editor Open Access

Nucleus accumbens-linked executive control networks mediating reversal learning in tree shrew brain

DEAR EDITOR,

Cognitive flexibility is crucial for animal survival but is frequently impaired in neuropsychiatric disorders. Although many brain structures and functional networks are involved in cognitive flexibility, the neural mechanisms underlying cooperation among specific functional networks remain unclear from a global perspective. In this study, [^{18}F]-fluorodeoxyglucose positron emission tomography (FDG-PET) was performed on 19 male tree shrews after four different visual discrimination tasks, including baseline, learning expert (LE), reversal naive (RN), and reversal expert (RE). Voxel-based analysis was used to identify the specific brain clusters corresponding to RN, LE, and RE, and the corresponding metabolic networks were subsequently constructed. Finally, potential dynamic combinations of brain structures dealing with contingencies and normal situations were explored. Intergroup comparison showed that the left nucleus accumbens (NAc) was activated in RN, and the network derived from the left NAc contained performance monitoring and executive control components of prefrontal cortex (PFC) regions as key nodes. The LE and RE networks contained key components of the memory system, including the amygdala and hippocampus, and PFC executive control systems that overlapped with the RN network. The reversal learning (RL) and learning processes were mediated by the interactions of multiple functional networks associated with performance monitoring, executive control, and memory systems. Notably, the NAc and PFC networks may act as functional interfaces in different systems to deal with contingencies and normal situations flexibly and effectively.

RL paradigms can be used to explore the neural mechanisms underpinning cognitive flexibility, which is crucial for animal survival and often disturbed in neuropsychiatric disorders. Previous studies have shown that efficient RL performance requires the participation of various functional brain systems, including neural correlates associated with internal and external environmental monitoring, reward, memory, and behavioral execution (Uddin, 2021). However, the core brain regions that trigger RL and how these functional systems cooperate to achieve RL remain unclear.

Here, we employed an RL paradigm based on visual discrimination using Bussey-Saksida Touch Screen Chambers (Campden Instruments Ltd., UK) (Mar et al, 2013) and [^{18}F]-fluorodeoxyglucose positron emission tomography (FDG-PET) brain imaging to explore longitudinal metabolic activity variation patterns in brain-wide networks. Chinese tree shrews (*Tupaia belangeri chinensis*), a close relative of primates with a well-developed brain structure and visual system, were applied as an animal model for the visual-based cognitive tasks (Schumacher et al, 2021; Yao, 2017). Considering the potential effects of sex hormones on female cognitive behavior (Hamson et al, 2016), only male tree shrews were included in this study. Nineteen domesticated adult male tree shrews (aged 8–12 months, obtained from the breeding colony at the Animal House Center of the Kunming Institute of Zoology, Yunnan, China) were trained to perform “go/no go” visual-discrimination tasks with “worm picture” and “apple picture” stimuli (Figure 1A). During training, the two visual cues were randomly displayed in two fixed touchscreen windows. When the correct picture was touched, the animal received a food reward, otherwise, the animal was punished by an audible sound and no reward.

Daily training was performed on each tree shrew and terminated after 30 min or 40 touches. In the initial training, the “worm picture” was set as the correct option. Animals were considered to have moved from the learning naive (LN) to LE stage after reaching >85% correct touch rate. After ca. six days of training, all 19 tree shrews reached the LE stage. An additional 5 days of training was performed to ensure stability

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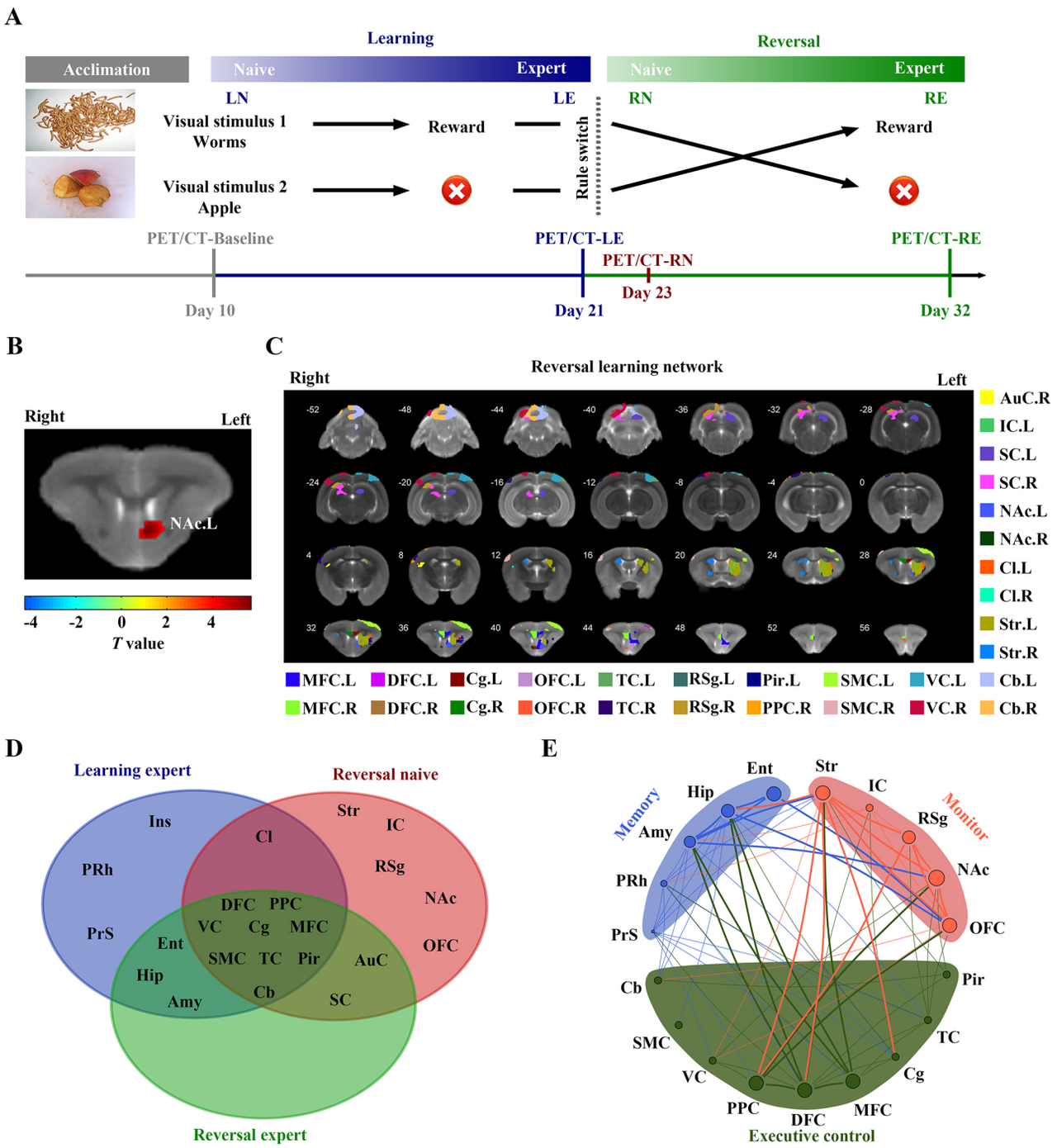

Figure 1 Variations in collaborative network patterns during visual discrimination learning and reversal learning (RL) in brains of tree shrews

A: Schematics of visual discrimination tasks and ^{18}F-FDG PET/CT imaging. B: Voxel-wise comparisons between RN and LE stage. Significant hyper-metabolism region was found in left NAc in RN stage (P<0.05, FWE-corrected, cluster size>50). T value, value of two-sample t-test. C: Sub-region location of RL network in tree shrew brain. D: Venn diagram showing overlap of metabolic networks involved in LE, RN, and RE stages. E: Schematic of functional systems engaged in dynamic visual discrimination tasks. LN, learning naive; LE, learning expert; RN, reversal naive; RE, reversal expert. MFC, medial frontal cortex; DFC, dorsal frontal cortex; Cg, cingulate cortex; OFC, orbital frontal cortex; TC, temporal cortex; RSg, retrosplenial granular cortex; Pir, piriform cortex; PPC, posterior parietal cortex; SMC, sensorimotor cortex; VC, visual cortex; AuC, auditory cortex; Ent, entorhinal cortex; Ins, insular cortex; PRh, perirhinal cortex; PrS, presubiculum; Hip, hippocampus; Amy, amygdala; IC, inferior colliculus; SC, superior colliculus; NAc, accumbens nucleus; Cl, claustrum; Str, striatum; Cb, cerebellum. L, left hemisphere; R, right hemisphere.

of the LE stage. On the last day of LE stage training, behavioral performance accuracy reached 95.64%±1.41% and trial number reached 38.00±1.05. Stimulus-reward mapping was then switched ("rule-switch") by setting the "apple picture" as the correct option. The tree shrews initially showed decreased performance after reversal, but eventually relearned the new stimulus-reward mapping from the RN to RE stages. After seven days of training, 15 of the 19 tree shrews reached the RN to RE performance criteria. On the last day of RE stage training, behavioral performance accuracy reached 91.71%±2.23% and trial number reached 39.13±0.84. The RN stage is a critical period for animal adaptation to rule switching, thus FDG-PET brain images obtained on the second day of rule switch training were selected as representative of the RN stage, with behavioral performance accuracy of 32.68%±4.87% and trial number of 20.87±3.14 (Supplementary Figure S1A, B). These behavioral data were further analyzed. When tree shrews reached either LE or RE, no significant differences were found in total training days (P=0.053, Student's t-test; Supplementary Figure S1C) or number of correct trials (P=0.812, Student's t-test; Supplementary Figure S1E). However, total number of trials (*: P=0.042, Student's t-test; Supplementary Figure S1D) and number of error trials (***: P<0.001, Student's t-test; Supplementary Figure S1F) during RL were significantly higher than during initial learning, which was to be expected as animals tend to persevere with original mapping before switching. The tree shrews showed good executive capacity in the RL paradigm, indicating their suitability as a model animal in visual-based decision-making studies (Mustafar et al, 2018).

Four FDG-PET/CT scans were performed during the baseline, LE, RN, and RE stages, respectively (see Supplementary Materials for details, Figure 1A). Compared to LE, tree shrews encountered an unexpected "rule-switch" in the RN stage, and significant hyper-metabolism was found in the left nucleus accumbens (NAc) (P<0.05, family-wise error (FWE) corrected; Figure 1B, Supplementary Figure S2A and Table S1). A significant positive correlation was found between the standard uptake value ratio (SUVR) of the left NAc and the error rate (P=0.001, Pearson correlation analysis; Supplementary Figure S3A). These results suggest that the left NAc may be involved in the reversed stimulus-reward process. As a major part of the ventral striatum, the NAc is regarded as an essential site for flexibly dealing with contingencies in both positive and negative situations (Floresco, 2015). Our results are consistent with previous brain lateralization studies showing that the left ventral striatum is critical for processing emotions elicited by food rewards (Güntürkün et al, 2020).

Therefore, the left NAc was selected as the seed region to generate a group-wide whole-brain metabolic connectivity map based on PET images at the RN stage. In detail, Pearson correlation coefficients were calculated between the SUVR of the seed region and every other voxel (Yakushev et al, 2017), with significance defined at P<0.05 (false discovery rate (FDR) corrected). Hence, a significant potential RL network was constructed (Figure 1C; Supplementary Table S2 and Figure S4). We then computed three different properties of the RL network during the baseline, LE, RN, and RE stages to examine network specificity. Average network degree, global efficiency, and synchronization of the RL network in the RN stage were all significantly higher than those in the other three stages (see Supplementary Materials for details; Supplementary Figure S5), suggesting that the RL network was functionally highly integrated in the RN stage. Furthermore, these results indicate that the RL network in the tree shrew brain specifically responds to "rule-switch". This RL network contained several prefrontal regions, consistent with the function of the PFC in error detection and value information storage (Izquierdo et al, 2017). Furthermore, corresponding key nodes of three PFC networks (i.e., fronto-parietal network (FPN), cingulo-opercular network (CON), and dorsal attention network (DAN)) were also contained in the RL network, including the dorsal frontal and posterior parietal cortices, cingulate and medial frontal cortices, and visual and dorsal frontal cortices, respectively (Menon & D'Esposito, 2022). This finding supports the view that the implementation of cognitive control in a constantly changing environment depends on the dynamic and flexible organization of the PFC networks (Menon & D'Esposito, 2022). More importantly, the recruitment of these PFC networks is closely related to NAc activation, reflecting the role of the NAc in triggering prefrontal functional networks to process contingencies.

To explore the potential dynamic interconnections of functional components that underpin cognitive status switching, we also constructed metabolic networks for the LE and RE stages (see Supplementary Materials for details, Supplementary Figures S6–S8). The learning networks in the LE and RE stages were nearly identical, and included cortical areas associated with executive control, such as the PFC, and classically recognized structures of the memory system, such as the hippocampus and amygdala (Figure 1D). This is not unexpected, as the animals were proficient at performing learned stimulus-reward mapping in both the LE and RE stages, which primarily involved stored-memory retrieval and behavioral execution. We also summarized the variations in brain networks in the LE, RN, and RE stages. The neural correlates involved in the three cognitive states represented the neural networks responsible for learned-memory storage and retrieval, internal and external environmental monitoring, and behavioral execution processing, respectively (Figure 1E). Interestingly, we found that the overlapping regions of the three metabolic networks contained key structures of the three PFC networks, as described above. Hence, the PFC functional networks were involved in both the performance of new learning and acquired cognitive task execution and may act as functional interfaces in different systems to deal with both contingencies and normal situations flexibly and effectively.

In conclusion, this study revealed that the NAc and core PFC executive control systems are involved in achieving RL. Multiple functional networks cooperate to accomplish a series of cognitive processes associated with RL, memory retrieval, performance monitoring, behavioral control, and updated memory storage. These findings highlight the complex brain network patterns of cognition and provide valuable hints regarding the potential pathophysiological sites associated with impaired cognitive flexibility in neuropsychiatric disorders.

SUPPLEMENTARY DATA

Supplementary data to this article can be found online.

COMPETING INTERESTS

The authors declare that they have no competing interests.

AUTHORS' CONTRIBUTIONS

T.T.P. and H.L. designed the experiment; T.T.P., C.L., and Q.X.Z. conducted the experiments; T.T.P., T.H.Z., W.Z., S.L.Z., and B.B.N. analyzed the data; D.M.L., G.H.Z., B.C.S., and L.X. conceived and supervised the project; T.T.P. and H.L. wrote the manuscript. All authors read and approved the final version of the manuscript.

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Nucleus accumbens-linked executive control networks mediating reversal learning in tree shrew brain

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Supplementary Materials

Animals

Domesticated adult male tree shrews (n=19, aged 8–12 months) were obtained from the breeding colony at the Animal House Center of the Kunming Institute of Zoology (Yunnan, China). The tree shrews were housed individually in a temperature-regulated room (25–27 ℃) with a regular day/night cycle (08:00–20:00). All animals had free access to water and food. The use and care of animals in this study conformed to the international guidelines and protocols approved by the Animal Care and Use Committee of the Kunming Institute of Zoology, Chinese Academy of Sciences (SMKX-20180806-177).

^{18}F-FDG Micro-PET/CT scanning and analysis

Four micro-PET/CT scans were performed during the baseline, learning expert (LE), reversal naive (RN), and reversal expert (RE) stages, respectively (Figure 1A). After intraperitoneal injection of 18F-FDG (185 MBq/kg), the animals were allowed to freely move around the experimental chamber without task as the baseline, or were subjected to a visual discrimination task (LE, RN, and RE) for 30 min. The tree shrews were then anesthetized with isoflurane (5% for induction and 1.5%–2.0% for maintenance) plus medical oxygen and placed in a prone position on the scanning bed of an E-plus 166 micro-PET/CT scanner (Institute of High Energy Physics, CAS, Beijing, China) (Huang et al, 2018). Scanning was performed for 20 min. The PET images were then reconstructed using the two-dimensional ordered subset expectation maximization algorithm with corrections for decay, normalization, dead time, photon attenuation, scatter, and random coincidence. The reconstructed image matrix size was 256×256×63 with a voxel size of 0.5×0.5×1.0 mm^3.

All images were preprocessed using an improved toolbox for voxel-wise analysis of tree shrew brain images based on SPM8 (Welcome Department of Cognitive Neurology) (Huang et al, 2018). Image preprocessing was performed as follows: (1) individual images of tree shrews were spatially normalized into stereotaxic space, (2) normalized images were smoothed with a 2.0×4.5×2.0 mm^3 Gaussian kernel, and (3) image intensity was globally normalized for each image.

Seed-based whole-brain metabolic connectivity analysis

A two-sample *t*-test was used to detect brain regions with significant differences in metabolism at the voxel level between different cognitive stages. The seed region of the reversal learning (RL) network was selected from clusters with significant metabolic differences between the RN and LE stages. To obtain specific spatial metabolic connectivity patterns of the seed regions, voxel-wise Pearson correlation coefficients were calculated between the seed region and all brain voxels based on brain metabolic imaging of the RN stage in an inter-subject manner (Carbonell et al, 2014; Tsai et al, 2020). After false discovery rate (FDR) correction, clusters in the generated brain-wide connectivity map were considered as brain regions highly correlated with the seed region. These brain regions constituted a potential metabolic network associated with visual discrimination RL.

Network analysis

The specificity of a functional network is often demonstrated by longitudinal comparisons of properties of networks across different cognitive states (Huang et al, 2020).

Average network degree (*K*)

The average degree of a network is commonly used as a measure of density, known as the network's total 'wiring cost', to assess the correlation strength of network internode connections (Huang et al, 2020). Average network degree was calculated as follows:

$$K = \frac{1}{N}\sum_i k_i$$

where K_i is the sum of weights attached to node *i* and *N* is the number of nodes.

Global efficiency (E_{glob})

Global efficiency measures the global information transfer ability of a network (Rubinov & Sporns, 2010) and is commonly used as a measure of network integration. Global network efficiency can be measured as:

$$E_{glob} = \frac{1}{N(N-1)}\sum_{i\neq j}\frac{1}{d_{ij}}$$

where d_{ij} is the shortest weighted path length between nodes *i* and *j*.

Synchronization (*S*)

Synchronization refers to the property of a network to synchronize in dynamics among coupled oscillators, which measures how likely it is that all nodes fluctuate in the same wave pattern. This property can be measured as (Wang et al, 2011):

$$S = \frac{\lambda_2}{\lambda_N}$$

where λ_2 and λ_N are the second smallest and largest eigenvalues of the coupling matrix *G*, respectively, defined as (Barahona & Pecora, 2002; Motter et al, 2005):

$$G_{ij}^W = \delta_{ij}\sum_{j=1}^{N} w_{ij} - w_{ij}$$

where w_{ij} is the $(i, j)^{\text{th}}$ element in the weighted network of *W*.

RL network responding to "rule-switch"

To examine the specificity of the potential RL metabolic network in tree shrews, we constructed the networks at the baseline, LE, RN, and RE stages (Supplementary Figure S5A-D). The average network degree (*K*) was significantly higher in RN than in the other stages (***P<0.001, permutation test; Supplementary Figure S5E). Global efficiency of the RL network was significantly higher in RN than in the other stages (***P<0.001, permutation test; Supplementary Figure S5F). In addition, synchronization of the RL network was higher in RN than in the other stages, and significantly higher than that in the LE stage (**P<0.01, permutation test; Supplementary Figure S5G).

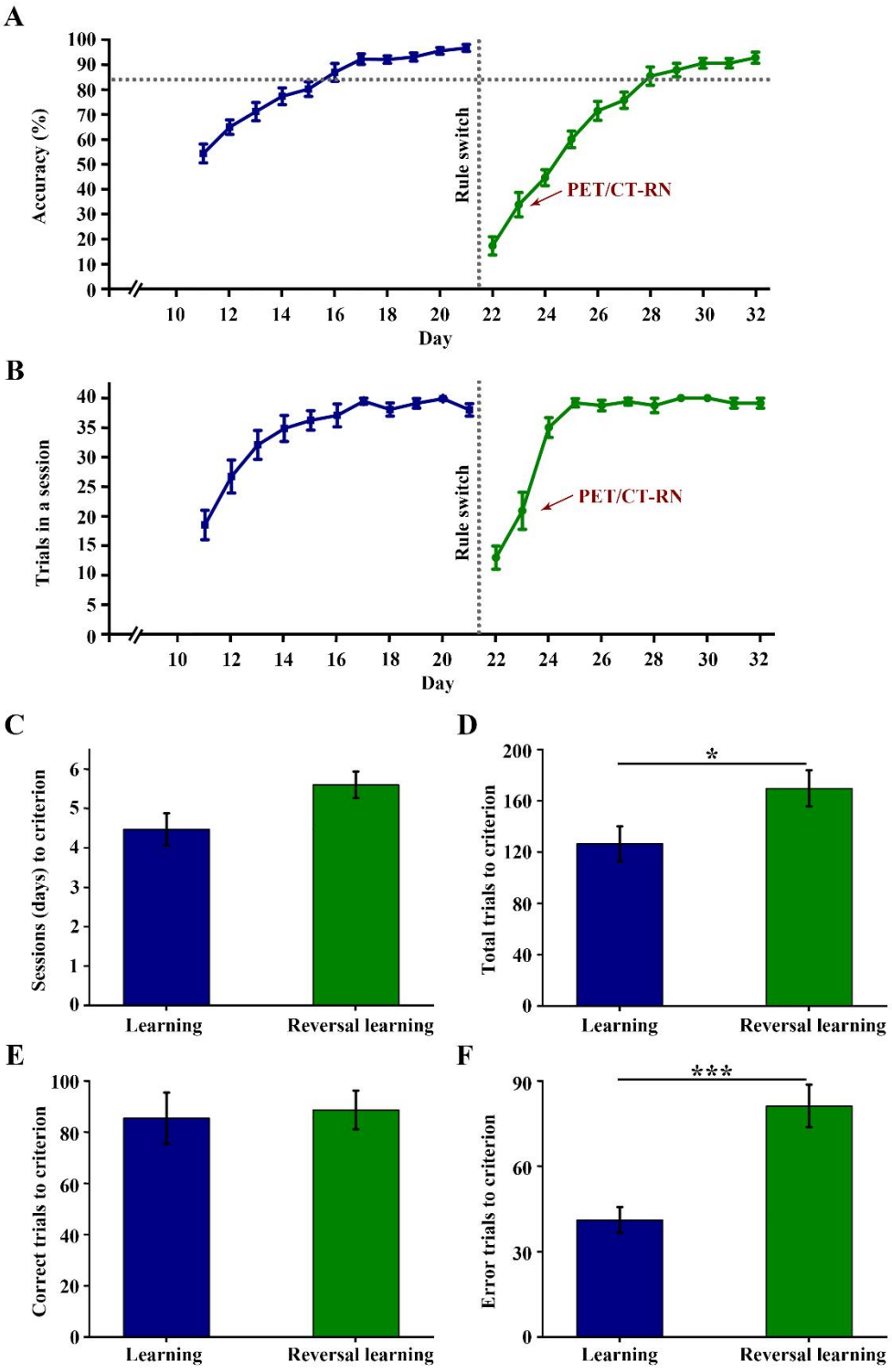
Composition of potential metabolic network associated with visual discrimination learning

The seed region of the learning network was selected from clusters with significant metabolic differences between the LE and baseline stages. Compared with the baseline stage, the LE tree shrews completed the visual discrimination learning task, with the probability that they touched the correct picture remaining above 85%. Based on two-sample *t*-test, a cluster located in the left entorhinal cortex (Ent) showed significantly elevated FDG uptake ($P<0.05$, family-wise error (FWE)-corrected; Supplementary Figure S2B, Supplementary Table S3). Furthermore, the standard uptake value ratio (SUVR) of this cluster showed a significant positive correlation with the measured behavior (correct rate) of the tree shrews ($r=0.405$; $P=0.004$, Pearson correlation analysis; Supplementary Figure S3B). Therefore, this cluster was selected as the seed region to explore the network involved in the visual discrimination learning task. A brain-wide metabolic connectivity map of the seed region was generated across subjects based on FDG-PET brain images in the LE stage. Brain clusters with suprathreshold metabolic connection strength were considered to constitute the potential learning network ($P<0.05$, FDR-corrected; Supplementary Figure S6A-B). The masks of the network members were given specific indices to generate a digital atlas of functional metabolic networks associated with visual discrimination learning (Supplementary Figure S6C). Details on the functional network members of visual discrimination learning are presented in Supplementary Table S4.

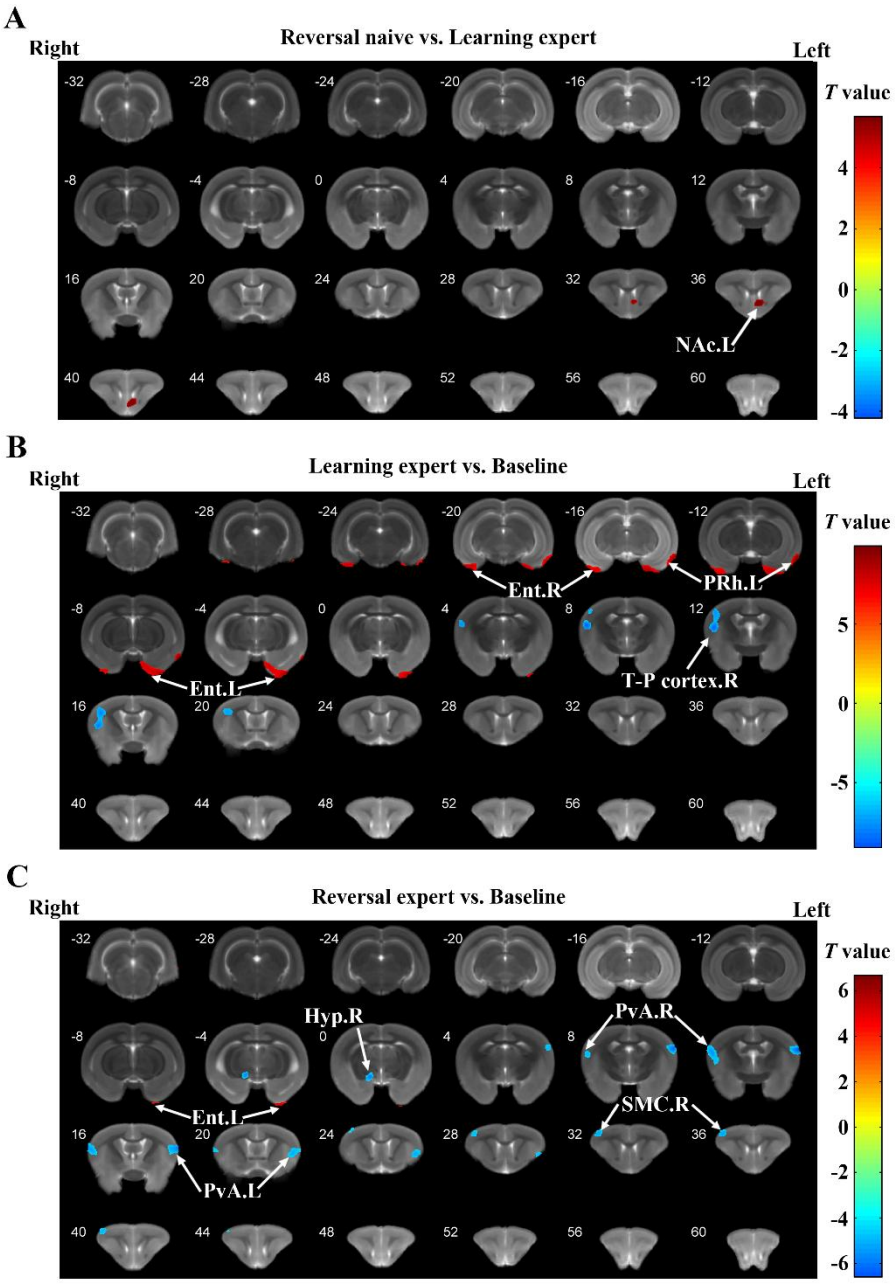
According to the differences between the RE and baseline stages (Supplementary Figure S2C, Supplementary Table S5), we selected the left Ent as the seed region to explore brain-wide metabolic connectivity based on PET images acquired in the RE stage (Supplementary Figure S7). Details on members of the visual discrimination learning metabolic network in the RE stage are shown in Supplementary Table S6.

Potential metabolic network associated with visual discrimination learning responding to task stages

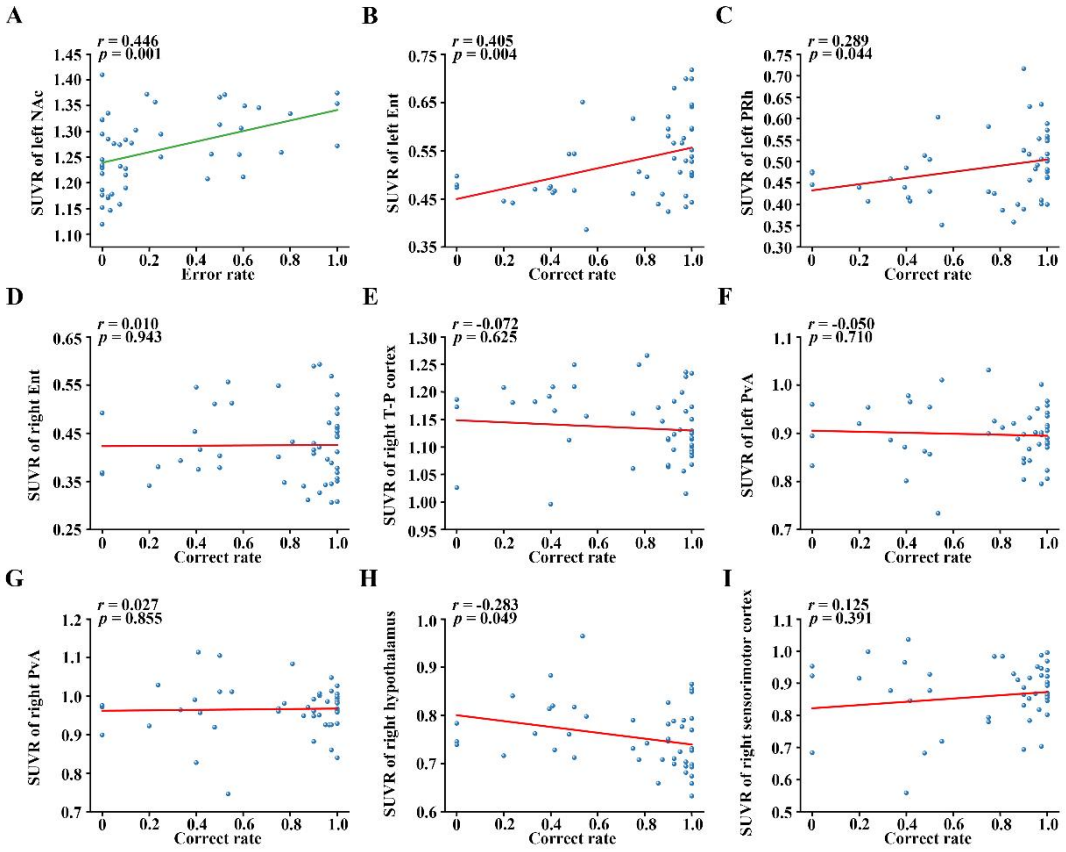
To examine the specific responses of the potential visual discrimination learning network to task stages, we examined the properties of the learning network in the baseline, LE, RN, and RE stages. As shown in the network connection strength schematic, metabolic correlations among nodes of the learning network in the LE, RN, and RE stages were stronger than those in baseline (Supplementary Figure S8A-D). Permutation tests revealed that the average network degree (K) was significantly higher in the LE, RN, and RE stages than in baseline (***$P<0.001$, permutation test; Supplementary Figure S8E). Global efficiency of the learning network in the LE, RN, and RE stages was significantly higher than in baseline (**$P<0.01$, ***$P<0.001$, permutation test; Supplementary Figure S8F). Additionally, synchronization of the learning network was also higher in the task stages than in the resting stage, with synchronization in the LE and RE stages significantly higher than that in the baseline stage (*$P<0.05$, permutation test; Supplementary Figure S8G). In brief, relative to the resting stage, the learning network exhibited significantly high connectivity and functional consistency in the task stages, indicating the specific response of the learning network to task stages.



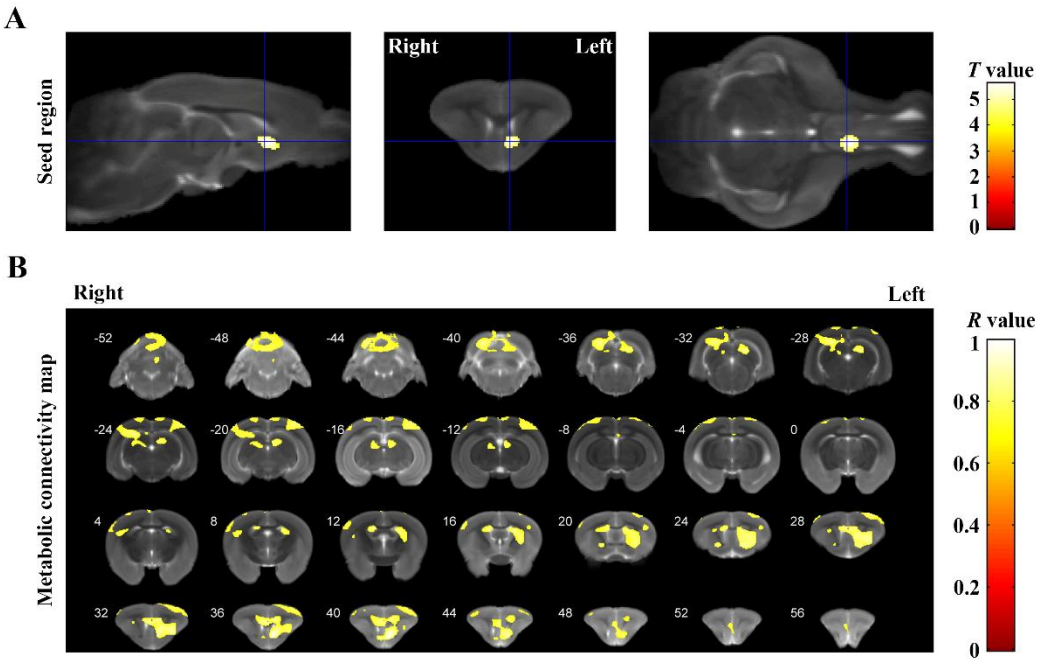
Supplementary Figure S1. Visual discrimination task behavioral performance in tree shrews. (A) Accuracy of each session. (B) Trial number in each session. (C) Number of training days, (D) total trials, (E) correct trials, and (F) error trials of tree shrews to reach task criteria. Error bars indicate standard errors. *P<0.05, ***P<0.001, Student's t-test.



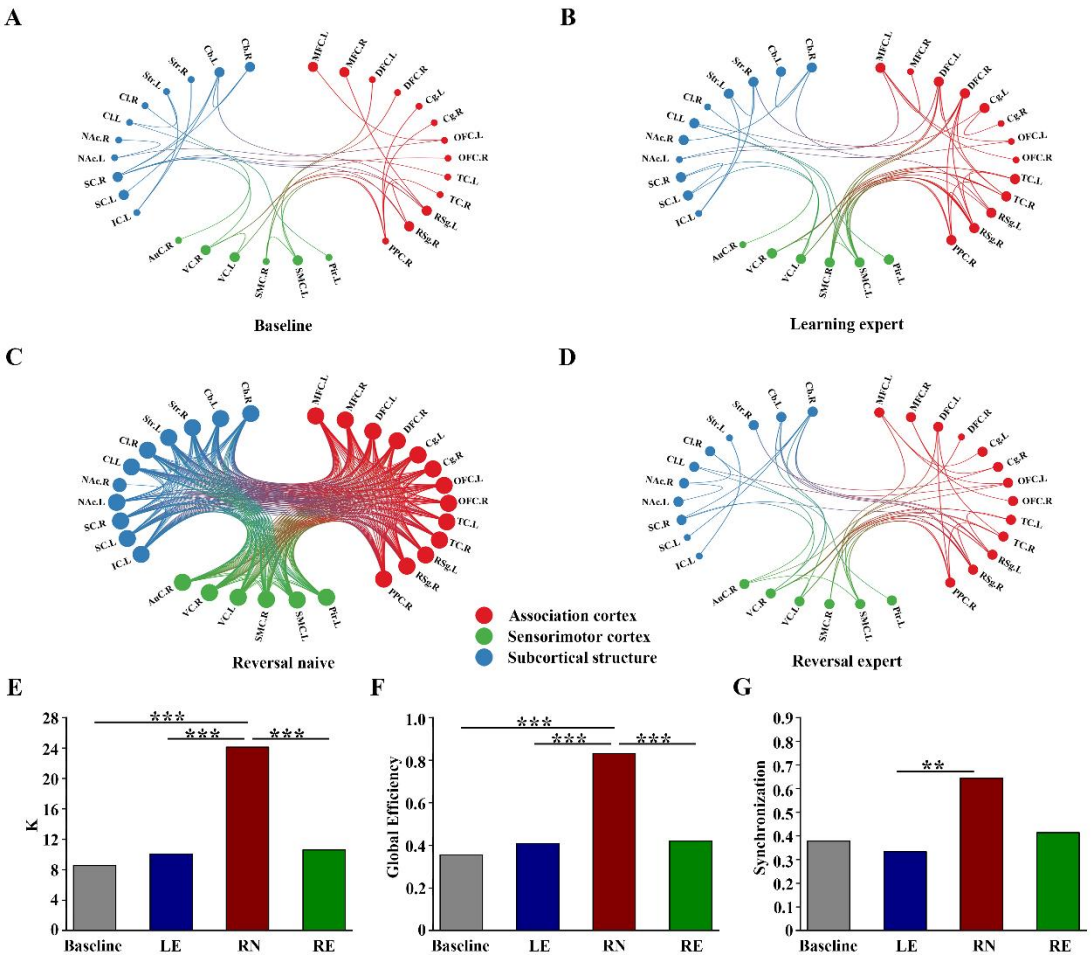
Supplementary Figure S2. Changes in glucose metabolism across different cognitive stages. (A) Voxel-wise comparison between RN and LE stage. Cluster with significant changes in glucose metabolism in RN state was located in left NAc (P<0.05, FWE-corrected, cluster size>50). (B) Voxel-wise comparison between LE and baseline stage. Clusters with significant changes in glucose metabolism in LE state were located in left Ent, left PRh, right Ent, and right temporal-parietal cortex (P<0.05, FWE, cluster size>50). (C) Voxel-wise comparison between RE and baseline stage. Clusters with significant changes in glucose metabolism in RE stage were located in left Ent, left PvA, right PvA, right Hyp, and right SMC (P<0.05, FWE-corrected, cluster size>50). Ent, entorhinal cortex; PRh, perirhinal cortex; T-P cortex, temporal-parietal cortex; NAc, accumbens nucleus; PvA, parietal ventral area; Hyp, hypothalamus; SMC, sensorimotor cortex. L, left hemisphere; R, right hemisphere.



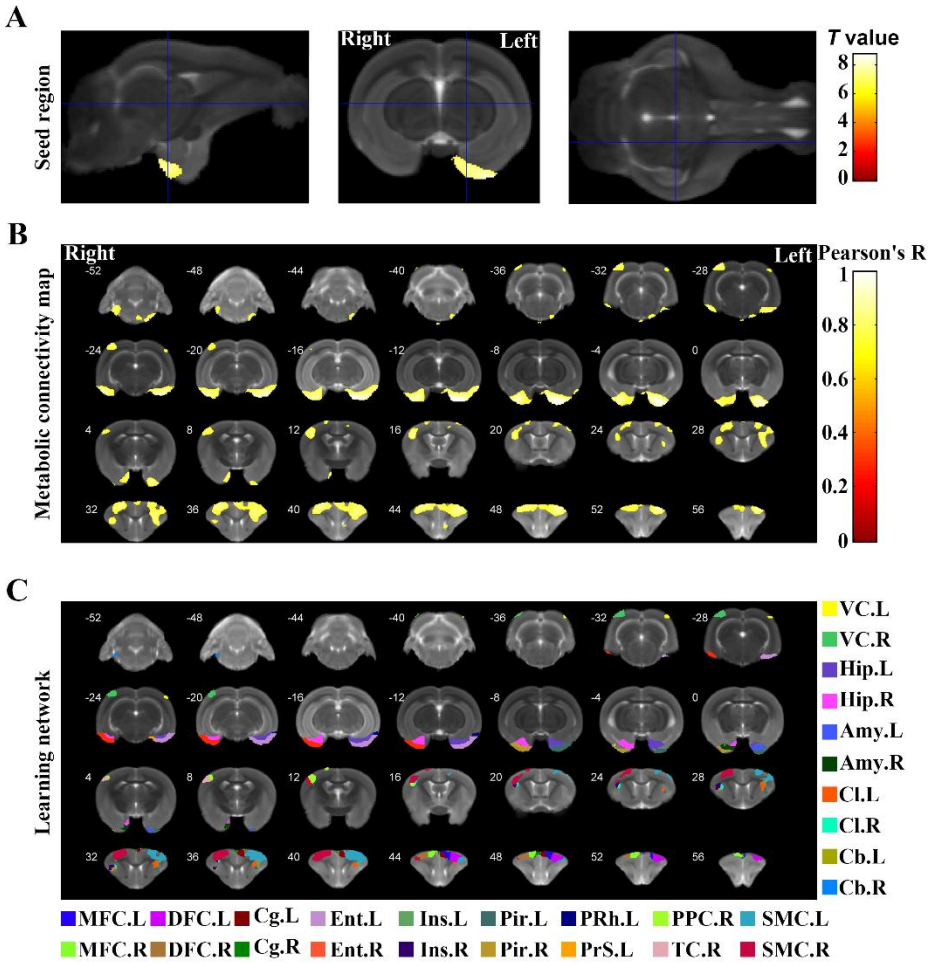
Supplementary Figure S3. Correlation between ^{18}F-FDG SUVR of brain clusters and measured behavior. SUVR, standard uptake value ratio, reference brain region was whole brain. Ent, entorhinal cortex; PRh, perirhinal cortex; T-P cortex, temporal-parietal cortex; NAc, accumbens nucleus; PvA, parietal ventral area; Hyp, hypothalamus; SMC, sensorimotor cortex. L, left hemisphere; R, right hemisphere. Pearson correlation analysis, significantly correlated parameters were set at $P<0.05$; r indicates Pearson correlation coefficient.



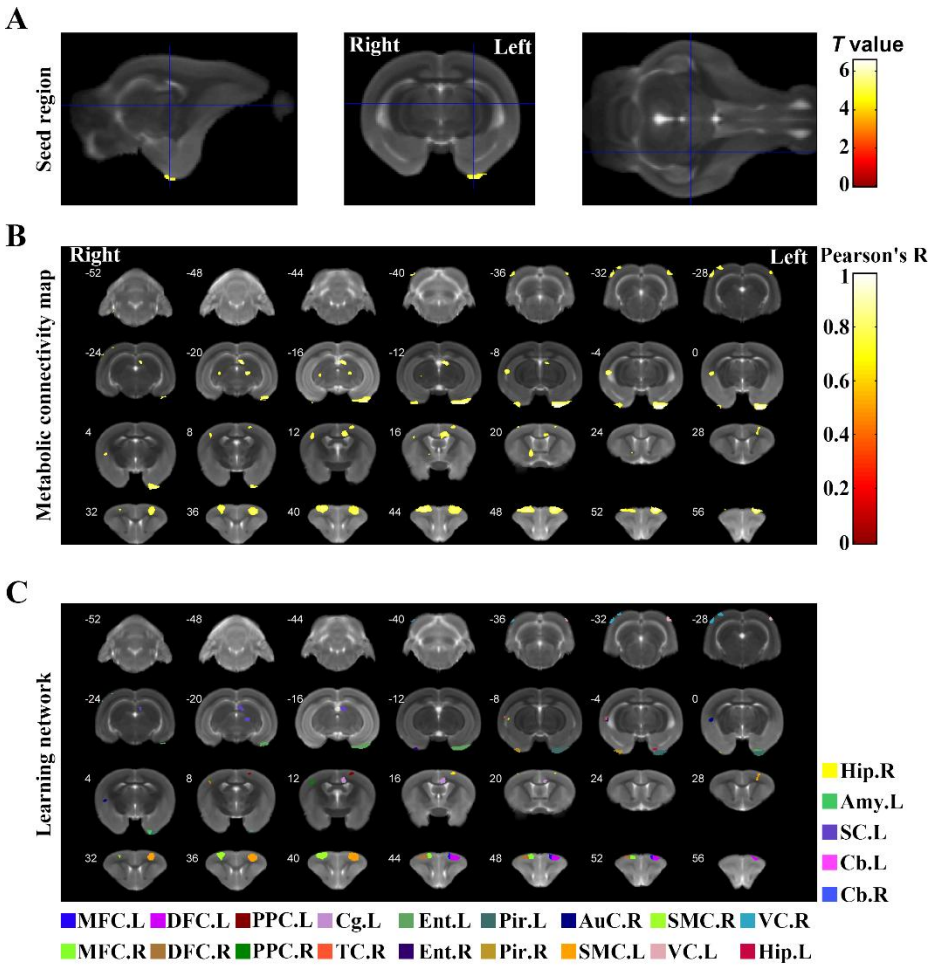
Supplementary Figure S4. Reversal learning metabolic network of tree shrew brain obtained in RN stage. (A) Left NAc was selected as a seed region. (B) Metabolic connectivity map of seed region in RN stage (P<0.05, FDR-corrected, cluster size>50). T value, value of two-sample t-test; R value, Pearson correlation coefficient.



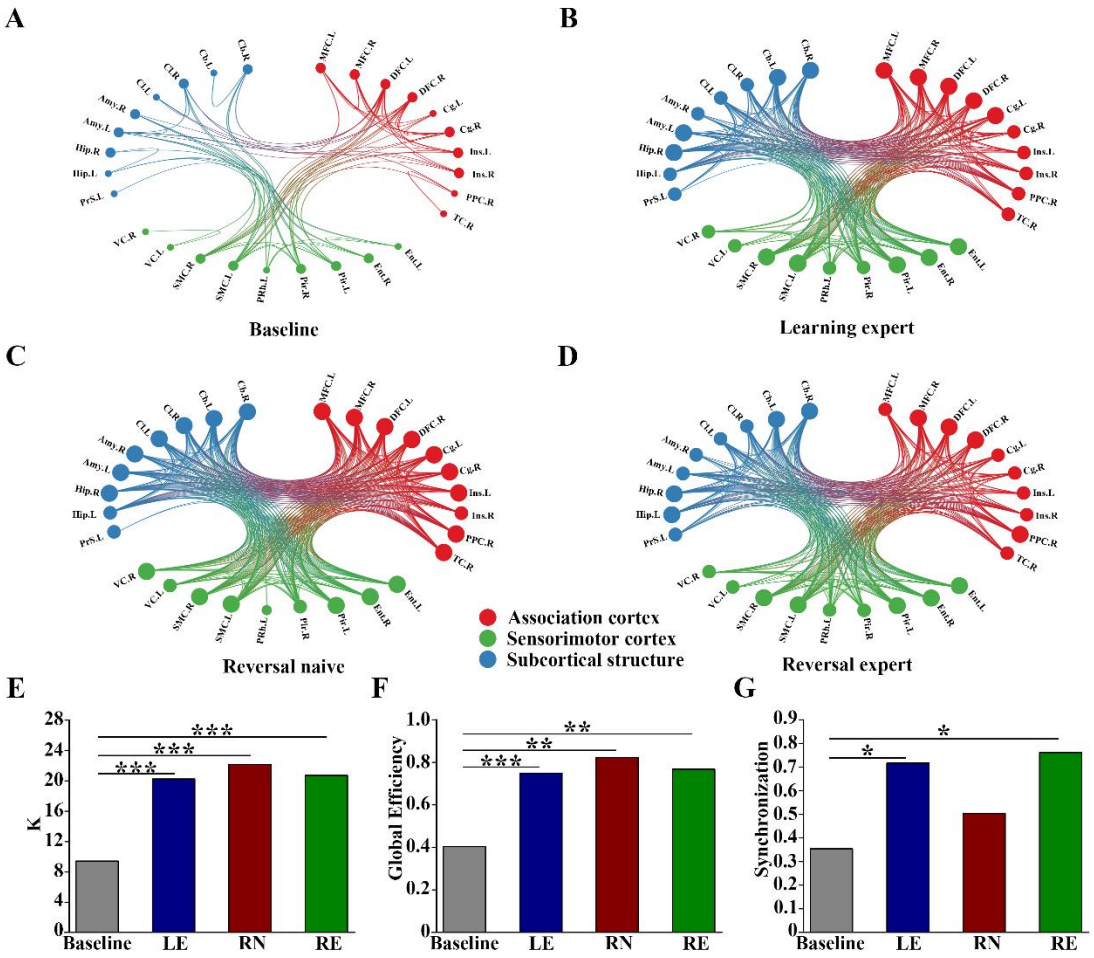
Supplementary Figure S5. Reversal learning (RL) network specifically responding to "rule-switch". Schematic of RL network metabolic connectivity in (A) baseline, (B) LE, (C) RN, and (D) RE stages. Size of ball indicates degree centrality of node. (E) Average network degree, (F) global efficiency, and (G) synchronization of RL network in four different cognitive stages. ***P*<0.01, ****P*<0.001, permutation test.



Supplementary Figure S6. Visual discrimination learning metabolic network of tree shrew brain obtained in LE stage. (A) Left entorhinal cortex was selected as a seed region. (B) Metabolic connectivity map of seed region in LE stage ($P<0.05$, FDR-corrected, cluster size>50). *T* value, value two-sample t-test; *R* value, Pearson correlation coefficient. (C) Sub-region location of visual discrimination learning network in tree shrew brain. Sub-functional region segmentation is presented in pseudocolor, whereas structural slices of tree shrew brains are presented in grayscale as background. Details on sub-functional regions are listed in bottom and right panels. MFC, medial frontal cortex; DFC, dorsal frontal cortex; Cg, cingulate cortex; Ent, entorhinal cortex; Ins, insular cortex; Pir, piriform cortex; PRh, perirhinal cortex; PrS, presubiculum; PPC, posterior parietal cortex; TC, temporal cortex; SMC, sensorimotor cortex; VC, visual cortex; Hip, hippocampus; Amy, amygdala; Cl, claustrum; Cb, cerebellum. L, left hemisphere; R, right hemisphere.



Supplementary Figure S7. Visual discrimination learning metabolic network of tree shrew brain obtained in RE stage. (A) Left entorhinal cortex was selected as a seed region. (B) Metabolic connectivity map of seed region in RE state (P<0.05, FDR-corrected, cluster size>50). T value, value of two-sample t-test; R value, Pearson correlation coefficient. (C) Sub-region location of visual discrimination learning network in tree shrew brain. Sub-functional region segmentation is presented in pseudocolor, whereas structural slices of tree shrew brains are presented in gray scale as background. Details on sub-functional regions are listed in bottom and right panels. MFC, medial frontal cortex; DFC, dorsal frontal cortex; Cg, cingulate cortex; Ent, entorhinal cortex; Pir, piriform cortex; AuC, auditory cortex; SC, superior colliculus; PPC, posterior parietal cortex; TC, temporal cortex; SMC, sensorimotor cortex; VC, visual cortex; Hip, hippocampus; Amy, amygdala; Cl, claustrum; Cb, cerebellum. L, left hemisphere; R, right hemisphere.



Supplementary Figure S8. Visual discrimination learning network specifically responding to task stages. Schematic of visual discrimination learning network metabolic connectivity in (A) baseline, (B) LE, (C) RN, and (D) RE stages. Size of ball indicates degree centrality of node. (E) Average network degree, (F) global efficiency, and (G) synchronization of visual discrimination learning network in four different cognitive stages. **P*<0.05, ***P*<0.01, ****P*<0.001, permutation test.

Supplementary Table S1. Significant changes in glucose metabolism in RN stage (RN vs. LE).

Region	Coordinate (mm)			Peak level		
	x	y	z	*T* value	*Z*-score	$P_{(FWE)}$
RN > LE						
Left accumbens nucleus	-1	7	4	5.62	4.80	0.006
RN < LE						
None						

Supplementary Table S2. Details on 30 brain structures in potential metabolic network associated with visual discrimination reversal learning. Nomenclature and abbreviations were adopted from histological atlas (L: left hemisphere, R: right hemisphere).

Brain regions	Abbreviations	Cluster size (mm^3)	Stereotaxic Coordinates (mm)		
			x	y	z
Medial frontal cortex	MFC.L	1320.86	-1	3	7
	MFC.R	1145.68	1	3	7
Dorsal frontal cortex	DFC.L	184.55	-4	4	7
	DFC.R	181.74	4	4	7
Cingulate cortex	Cg.L	373.78	-1	4	7
	Cg.R	441.22	1	4	7
Orbital frontal cortex	OFC	355.04	-1	6	7
	OFC	187.36	1	6	7
Temporal cortex	TC.L	511.48	-8	5	-4
	TC.R	1249.67	8	5	-4
Retrosplenial granular cortex	RSg.L	266.98	-1	3	-4
	RSg.R	1856.7	1	4	-4
Piriform cortex	Pir.L	799.08	-5	10	0
Posterior parietal cortex	PPC.R	414.99	6	2	-3
Sensorimotor cortex	SMC.L	3022.06	-4	2	1
	SMC.R	756.92	4	2	1
Visual cortex	VC.L	2956.48	-4	1	-6
	VC.R	3187.87	4	1	-6
Auditory cortex	AuC.R	148.95	8	8	-2
Inferior colliculus	IC.L	477.76	-2	7	-10
Superior colliculus	SC.L	2654.84	-3	5	-7
	SC.R	3053.91	3	5	-7
Accumbens nucleus	NAc.L	666.99	-1	7	4
	NAc.R	100.24	1	7	4
Claustrum	Cl.L	547.08	-3	5	4
	Cl.R	116.16	3	5	4

Striatum	Str.L	5802.43	-3	5	3
	Str.R	1200.95	3	5	3
Cerebellum	Cb.L	3728.39	-5	9	-11
	Cb.R	2238.91	5	9	-11

Supplementary Table S3. Significant changes in glucose metabolism LE stage (LE vs. baseline).

Region	Coordinate (mm)			Peak level		
	x	y	z	*T* value	*Z*-score	$P_{(FWE)}$
LE > Baseline						
Left entorhinal cortex	-5	14	-4	8.73	6.36	0.00
Left perirhinal cortex	-9	9	-6	8.51	6.26	0.00
Right entorhinal cortex	5	13	-5	7.87	5.96	0.00
LE < Baseline						
Right temporal-parietal cortex	7	5	-2	8.94	6.45	0.00

Supplementary Table S4. Details on 28 brain structures of potential metabolic network associated with visual discrimination learning obtained during LE stage. Nomenclature and abbreviations were adopted from histological atlas (L: left hemisphere, R: right hemisphere).

Brain regions	Abbreviations	Cluster size (mm^3)	Stereotaxic Coordinates (mm)		
			x	y	z
Medial frontal cortex	MFC.L	734.44	-1	3	7
	MFC.R	1099.78	1	3	7
Dorsal frontal cortex	DFC.L	1974.74	-4	4	7
	DFC.R	816.87	4	4	7
Cingulate cortex	Cg.L	1111.96	-1	4	7
	Cg.R	442.16	1	4	7
Entorhinal cortex	Ent.L	3726.52	-7	12	-6
	Ent.R	3077.33	7	12	-6
Insular cortex	Ins.L	310.07	-5	5	4
	Ins.R	559.26	5	5	4
Piriform cortex	Pir.L	2058.11	-5	10	0
	Pir.R	1551.31	5	10	0
Perirhinal cortex	PRh.L	492.75	-9	10	-5
Presubiculum	PrS.L	208.9	-5	10	-7
Posterior parietal cortex	PPC.R	974.25	6	2	-3
Temporal cortex	TC.R	368.16	8	5	-4
Sensorimotor cortex	SMC.L	5156.05	-4	2	1
	SMC.R	5183.21	4	2	1
Visual cortex	VC.L	354.1	-4	1	-6
	VC.R	1481.99	4	1	-6
Hippocampus	Hip.L	3905.44	-4	12	-5
	Hip.R	3241.27	4	12	-5
Amygdala	Amy.L	766.29	-4	12	-1
	Amy.R	1078.24	4	12	-1
Claustrum	Cl.L	989.24	-3	5	4

	Cl.R	298.83	3	5	4
Cerebellum	Cb.L	785.02	-5	9	-11
	Cb.R	1697.45	5	9	-11

Supplementary Table S5. Significant changes in glucose metabolism RE stage (RE vs. baseline).

Region	Coordinate (mm)			Peak level		
	x	y	z	*T* value	*Z*-score	$P_{(FWE)}$
RE > Baseline						
Left entorhinal cortex	-4	14	-4	5.19	4.39	0.05
RE < Baseline						
Left parietal ventral area	-8	5	0	6.50	5.15	0.002
Right hypothalamus	2	10	-3	6.32	5.06	0.004
Right parietal ventral area	8	5	-1	5.57	4.62	0.023
Right sensorimotor cortex	6	2	3	5.44	4.55	0.03

Supplementary Table S6. Details on 22 brain structures of potential metabolic network associated with visual discrimination learning obtained during RE stage. Nomenclature and abbreviations were adopted from histological atlas (L: left hemisphere, R: right hemisphere).

Brain regions	Abbreviations	Cluster size (mm^3)	Stereotaxic Coordinates (mm)		
			x	y	z
Medial frontal cortex	MFC.L	182.67	-1	3	7
	MFC.R	420.62	1	3	7
Dorsal frontal cortex	DFC.L	880.58	-4	4	7
	DFC.R	444.97	4	4	7
Cingulate cortex	Cg.L	461.83	-1	4	7
Entorhinal cortex	Ent.L	1378.00	-7	12	-6
	Ent.R	170.49	7	12	-6
Piriform cortex	Pir.L	1179.40	-5	10	0
	Pir.R	280.10	5	10	0
Auditory cortex	AuC.R	236.07	8	8	-3
Superior colliculus	SC.L	437.48	-3	5	-6
Posterior parietal cortex	PPC.R	171.43	6	2	-3
Temporal cortex	TC.R	100.24	8	5	-4
Sensorimotor cortex	SMC.L	1598.20	-4	2	1
	SMC.R	989.24	4	2	1
Visual cortex	VC.L	199.53	-4	1	-6
	VC.R	502.12	4	1	-6
Hippocampus	Hip.L	141.45	-4	12	-5
	Hip.R	100.32	4	12	-5
Amygdala	Amy.L	240.75	-4	12	-1
Cerebellum	Cb.L	108.99	-5	9	-11
	Cb.R	960.20	5	9	-11

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