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A Metabolomics-based Approach for Ranking the Depressive Level in Chronic **Unpredictable Mild Stress Rat Model** Xinyu Yu^{a,1}, Shanlei Qiao^{a,b,1}, Di Wang^a, Jiayong Dai^a, Jun Wang^b, Rutan Zhang^a, Li Wang^a, Lei Li^a ⊠ ^aDepartment of Hygiene Analysis and Detection, School of Public Health, Nanjing Medical University, Nanjing, Jiangsu 211166, P. R. China ^bThe Key Laboratory of Modern Toxicology, Ministry of Education, School of Public Health, Nanjing Medical University, Nanjing 211166, Jiangsu, P.R. China. 1 Authors contributed equally. [™]*Corresponding authors:* Lei Li, Department of hygiene analysis and detection, School of Public Health, Nanjing Medical University, 101 Longmian Avenue, Nanjing 211166, P. R. China Tel: +86-25-8686-8404; Fax: +86-25-8686-8499; E-mail: drleili@hotmail.com

33 Abstract

34 An untargeted metabolomics study to investigate the metabolome change in plasma, hippocampus and prefrontal 35 cortex (PFC) in animal model of major depressive disorder (MDD) had been conducted. Metabolomic profiling for 36 the different bio-samples was analyzed by using Ultra-High Performance Liquid Chromatography coupled with 37 Orbitrap mass spectrometry (UPLC-Orbitrap-MS). Behavioral tests were applied to evaluate the depressive degree 38 and antidepressive effect. Then the univariate and multivariate statistics including Student's t-test, principal 39 component analysis (PCA) and partial least squares discriminant analysis (PLS-DA) were applied to reveal the 40 metabolic differences between control, model and antidepressive-treated group. Metabolomics analysis 41 demonstrated that MDD was a kind of systemic disease in which disturbance of neuroendocrinology, amino acid 42 metabolism, energy metabolism, lipid metabolism and synthesis of neurotransmitter were involved. The 43 significantly changed metabolites acquired from the statistical method were identified and a simplified panel 44 which consisted of 6 metabolites including L-tryptophan, L-kynurenine, quinolinic acid, L-phenylalanine, 45 gamma-aminobutyric acid and N-Acetylaspartic acid was obtained. In combination with the results of sucrose 46 preference test, a new PLS-DA model conducted by the identified changed metabolome showed a good predictive 47 power which meant the metabolome was able to rank the depressive level as the behavioral test. Then correlational 48 analysis indicated the simplified panel in plasma had a relative good correlation with that in hippocampus and PFC. 49 This study offers a new strategy for characterization of endogenous metabolic perturbations by a metabolomics 50 method and the good predictive power and correlation for the significantly changed metabolome between plasma 51 and brain regions might be helpful in ranking the depressive level in CUMS model. These results are helpful in 52 further study to develop a noninvasive and exact diagnostic approach by an objective laboratory-based test through 53 the metabolomics platform.

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⁵⁴ Key words: metabolomics; Chronic unpredictable mild stress; UPLC-Orbitrap-MS; Biomarkers

63 1. Introduction

64 Major depressive disorder (MDD) is a complex psychiatric illness which is often related to various stressful 65 events in our daily life and it has been regarded as one of the most common mental diseases around the world for 66 the prevalence of 15%-20%¹. It has greatly influenced the life quality of more than 350 million depressive patients 67 and it is known as one of the vital cause of disability worldwide². Different kinds of stressful events is experienced 68 in all human subjects during their lifetimes which can affect multiple biochemical systems and finally leads to several diseases³⁻⁵. Moreover, it has been reported that the stressors, especially for those chronic, low intensity 69 70 stressful events are the most likely catalyst in the etiology of MDD⁶. For simulation of diverse chronic stressful 71 events exposure, chronic unpredictable mild stress (CUMS) model has been established and in this model, animals 72 are sequentially exposed to a series of chronic mild stressors for several weeks which aims to mimic the stress of human society7. Therefore, CUMS model has been regarded as one of the most valid and reliable animal models 73 74 and has been wildly applied for the further research of MDD.

75 Metabolomics, which focuses on qualitative analysis of metabolites in biological samples at the global level, 76 has emerged as a powerful tool in the investigation of significant biochemical alterations. It has been applied for 77 capturing disease-specific metabolomic signatures and then searching for potential biomarkers in combination with 78 multivariate statistical methods which can provide new insight into deeper understanding of the pathological mechanisms for diseases^{5,8}. In previous research, our group has successfully established a urine-based metabolic 79 80 profiling approach in CUMS rats by UPLC-MS⁹, however, current researches are mostly focused on a single 81 sample such as urine, plasma or the brain tissue which can't reflect the dynamic and systemic metabolic changes in 82 the pathological process of MDD.

Researches have shown that the hippocampal function is closely related to short-term memory and learning capacity, and the nerve cells in hippocampus are extremely sensitive to stress. Besides, it has been reported that stress can also do great harm or even cause neuronal apoptosis in certain brain regions, especially for hippocampus. Moreover, the Magnetic Resonance Imaging (MRI) of the depressive patients also demonstrated a reduction in the volume of hippocampus¹⁰⁻¹². So there is increasing evidence indicated that hippocampus plays an important role in the pathogenesis of depression.

The prefrontal cortex (PFC) is one of the last brain regions to mature fully during ontogenesis which plays a key role in regulation function in central nervous system. The function of PFC is mainly associated with long-term memory, expression of emotions and spatial cognition and it was very sensitive to various damage¹³. The dysfunction of PFC have been proved to have a close relationship with many psychiatric disorders including

93 post-traumatic stress disorder, bipolar disorder and MDD. The working memory which could be defined as the 94 gradual development of memory system from short-term to long-term memory and it was more closely correlated 95 to PFC than hippocampus and basal ganglia¹⁴. Electrophysiological and neuroimaging studies had been applied to 96 explore the function of PFC in the formation of long-term memory and pathogenesis for diseases and indicated that 97 due to the character of pyramidal neuron in PFC, it could keep the message even when stimulus disappeared^{15, 16}. It 98 had been reported that there was a decreased cerebral blood flow along with the energy metabolic disturbance in 99 MDD patients, and neuroimaging indicated a reduction in volume for PFC grey matter¹⁶. Besides, dysfunction of 100 neurotransmitters and metabolic changes for amino acid was observed by metabolomic methods in CUMS 101 animals¹⁷.

However, the essential prerequisites for the biomarkers which can be applied in the diagnosis of diseases are that they are of relatively high sensitivity and accuracy, and the testing sample should be easily obtained. For MDD, brain biopsy samples are neither practical nor convenient, while for plasma samples, it can be easily collected at minimal risk and cost to the patient. So it is necessary to explore whether the metabolic changes in plasma are consistent with those in brain, especially in hippocampus and PFC.

107 In this study, we collected three kinds of samples, plasma, hippocampus and PFC from control, CUMS model 108 and antidepressant-treated rats in order to investigate the pathogenesis of MDD according to the metabolome 109 change from peripheral blood to CNS by a UPLC-Orbitrap-MS based metabolomics platform. Then we also aimed 110 to establish an objective method to rate the level of depression by matching results of behavioral test and the 111 changed-metabolome. Finally, according to the mutual changed metabolites in three kinds of samples, we 112 simplified the biomarkers to a panel, and then explored whether changed level of metabolites in the simplified 113 panel was associated with results of behavioral test. In order to investigate whether it was practical to use the 114 simplified panel in plasma to represent that in brain, correlation analysis was also performed to explore the 115 relationship between the panels in three kinds of samples.

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117 2. Materials and Methods

118 2.1 Chemicals and Reagents

HPLC grade methanol, acetonitrile and formic acid were purchased from Merck (Merck, Darmstadt,
Germany). Deionized water was produced by Milli-Q50SP Reagent system (Millipore Corporation, MA, USA).
Paroxetine hydrochloride was obtained from Sigma-Aldrich (MO, USA). The enzyme linked immunosorbent
assay (ELISA) kits of rat IL-6 and TNF-α were obtained from 4A biotech Co.Ltd. (Beijing, China).

123 2.2 Animals

30 male Wistar rats, weighing 100 ± 10 g were commercially purchased from Shanghai Laboratory Animal Co. Ltd. (SLAC, Shanghai, China). All rats were housed individually and kept at a laboratory animal barrier system with required environment (temperature of $24\pm1^{\circ}$ C, relative humidity of $45\pm15^{\circ}$, and a 12h light/dark cycle). Rats were allowed to acclimatize the environment for two weeks and during this period, every rat had free access to standard rat chow and tap water. The study was approved by national legislations of China and local guidelines and the experiments were performed according to a protocol approved by the Nanjing Medical University Institutional Animal Care and Use Committee.

131 2.3 Chronic unpredictable mild stress (CUMS) protocol

132 After two weeks of acclimatization, the rats were firstly trained to consume the 1% sucrose solution, and this 133 training lasted for three weeks. During the training period, the sucrose preference test (SPT) was conducted twice a 134 week in the first 2 weeks and once in the last week until the sucrose preference (SP) of each rat was stable. Then 135 the rats were randomly divided into three groups, control group, model group and model group treated with 136 paroxetine, and each group contained 10 rats. During the whole experience, rats in control group were fed with 137 food and tap water ad libitum, except for a 20h food and water deprivation before each SPT. According to the 138 experimental design shown in Fig.1, in the first three weeks, rats in model and treated group were exposed to a 139 series of chronic unpredictable mild stressors according to the protocol which has been changed slightly. The 140 stressors consisted of 45° cage tilting along the vertical axis, paired housing, food or/and water deprivation, 141 stroboscopic illumination (200 flashes/min), soiled cage (300 ml water spilled into the padding), continuous 142 overnight illumination, and white noise (85db). The detailed schedule was displayed in S-Table.1. Then, rats in 143 treated group received antidepressive drug administration, and rats in both model and treated group were still 144 exposed to the CUMS procedure in the next 4 weeks. The paroxetine was dissolved in physiological saline and 145 administrated intraperitoneally at the dosage of 10mg/kg at 9:00 every morning. Rats in another two groups 146 received administration of physiological saline in the same volume.

147 2.4 Behavioral test

148 2.4.1 Sucrose preference test

According to Willner who firstly conducted the CUMS model, the Sucrose preference test (SPT) was selected as an intuitively measurement of anhedonia in rats which exposed to a series of stressors^{18, 19}. Before each test, all rats were deprived of water and food for 20h, then they were put into individual cages and provided with two bottles of different solution, tap water and 1% sucrose solution. During this 2-hour-long test, rats were staying in

- 153 normal environmental without any stressors mentioned above and they had free access to two kinds of solution.
- 154 Bottles with tap water and sucrose solution were switched once an hour to avoid the place preference.
- 155 The SP means the ratio of consumed 1% sucrose solution relative to that of total solution in the test, and can
- be calculated according the formula below:
- 157 SP = sucrose consumption/ (sucrose consumption + water consumption) *100%

158 2.4.2 Open-field test

The open-field test (OPT) was conducted to evaluate the ability of spatial exploration²⁰. All rats were transferred to a quiet operating room (<65d) 30min before each test for acclimatization and then the test was conducted between 13:00 and 16:00. Each rat was gently put into the test field which consisted of black background marked with a grid dividing it into 25 equal-size squares (100*100 cm²) and a 40-cm-high wall. After adaption for 30s, then the rats took the 5-minutes-long test, and a record was kept of the locomotor activity such as the time spent in the center square and the frequency of rearing (standing upright on one's hind paws). After each rat' test, the open field was clean by 75% ethanol to eliminate the smell and faeces.

166 2.4.3 Forced swimming test

167 The forced-swimming test (FST) was performed as a valid measurement when evaluating the status of 168 depression for animals undergoing CUMS procedure²¹. Rats were individually put into Plexiglas cylinders (50cm 169 in height and 18cm in diameter) which filled with water $(25\pm1 \text{ }^{\circ}\text{C})$ up to a height of 20cm. The cylinder was 170 thoroughly cleaned after each test. During the 5-minutes-long test, the total immobility time was recorded with the 171 help of chronograph.

172 2.4.4 Food consumption and body weight.

During the whole experiment, the consumption of chow for each rat was recorded, and specifically, at 17:00 every afternoon, fresh chow was weighed and added into the feeding trough, then after 24h, we removed the uneaten chow and weighed it. Food consumption was recorded everyday as a measurement of appetite and body weight of each rat was recorded once a week.

177 2.5 Statistical Analysis for behavioral data

All data from behavioral test was expressed in the form of mean±standard deviation. The statistical analysis
was carried out by using SPSS 17.0 software (Chicago, IL, USA). The results of OPT was non-normal-distributed
so the Kruskal-Wallis test was applied to analyze it, while for the results of other behavioral tests including SPT,
FST, food consumption and body weight, they were analyzed by one-way analysis of variance (ANOVA) followed
by post hoc LSD test. The significance level was set at p<0.05.

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2.6 Sample collection and preparation

184	According to the experimental schedule, as soon as the final behavioral test finished, the blood samples were
185	obtained from portal vein and collected in heparin sodium anticoagulation tubes. Then rats were sacrificed and the
186	hippocampus and PFC were dissected from brain on ice, weighed, frozen with liquid nitrogen rapidly. The blood
187	samples were firstly centrifuged at 3000 rpm for 10 minutes and then collected the supernatant. All the samples
188	were stored at -80°C immediately.
189	Prior to analysis, all samples were thawed at room temperature for the following preparation. 500µl plasma
190	samples were mixed with acetonitrile at the ratio of 1:3 (v/v) and centrifuged at 12,000 rpm for 20 minutes to
191	remove large-molecular-weight proteins. Then the supernatants were diluted with water at a ratio of 1:3 (v/v) again
192	and transferred to vials for metabolomic profiling.
193	For hippocampus and PFC samples, 20mg of each sample was transferred to a 2ml centrifuge tube and mixed
194	with 1ml extracting solution of water-acetonitrile-chloroform (2:5:2, $v/v/v$). The mixture was then blended by
195	Tissue Lyser II (Dusseldorf, Germany) at the frequency of 50Hz for 15 minutes, subsequently centrifuged at
196	12,000 rpm for 10 min and 600μ l supernatant was transferred to vial for analysis.
197	2.7 UPLC-Orbitrap-MS analysis
198	The chromatographic separation was performed on a UPLC Ultimate 3000 system (Dionex, Germering,
199	Germany) equipped with a 1.9 μ m Hypersile Gold C ₁₈ column (100mm×2.1mm) (Thermo Fisher Scientific), and
200	the column was maintained at 40°C. A multistep gradient consisted of 0.1% formic acid in water (A) and 0.1%
201	formic acid in acetonitrile (B) had been applied and the gradient operated at a flow rate of 0.4 mL/min by linearly
202	increasing solvent B from 5% to 95% over 15 min, then the column was washed with 95% solvent B for 2 min and
203	re-equilibrated in 5% solvent B. The UPLC autosampler temperature [Ultimate WPS-3000 UPLC system (Dionex,
204	Germering, Germany)] was set at 4°C and the injection volume for each sample was 5 µL.
205	MS data were collected by the Orbitrap mass spectrometer (Thermo Fisher Scientific, Bremen, Germany)
206	equipped with a heated electrospray source (HESI) at the resolution of 700,000 in both positive and negative mode
207	simultaneously. For both positive and negative mode, the operating parameters were set as follows: a spray voltage
208	of 3 kV, the capillary temperature of 300°C, sheath gas flow of 40 arbitrary units, auxiliary gas flow of 10 arbitrary
209	units, sweep gas of 2 arbitrary units and S-Lens RF level of 50. In the full scan analysis (70 to 1050 amu), the
210	resolution was set at 700,000 with an automatic gain control (AGC) target of 1×10 ⁶ charges and a maximum
211	injection time (IT) of 120 ms. Both the UPLC and the Orbitrap mass spectrometer system were controlled by the
212	Xcalibur 2.2 software (Thermo Fisher Scientific).

The quality control (QC) samples had been prepared by pooling same volume of supernatant from samples of plasma, hippocampus and PFC, respectively and were pretreated in the same manner as real samples, then analyzed every 10 samples to ensure the stability and repeatability. The mass spectrometry was calibrated every 24 hour during the profiling to ensure the mass accuracy.

217 2.8 Data analysis

218 All of the raw data files were introduced to the SIEVE software (Thermo Fisher Scientific) where data 219 pretreatment including peak realignment, baseline correction and peak deconvolution had been done. After data 220 pretreatment, a table which was organized into a three-dimensional matrix consisted of sample names 221 (observations), annotated peak indices (RT-m/z pairs) and the intensity of each sample (i.e. peak area) had been 222 obtained. The data was then mean-scaled and imported into the SIMCA-P 13.0 software (Umetrics, Umea, Sweden) 223 for multivariate statistics such as principal component analysis (PCA) and partial least squares discriminant 224 analysis (PLS-DA). PCA reduced high dimensional spectral variation into a two or three principal components 225 without losing the vast majority of information, and then the score map visualized the distribution of the clustering 226 or the grouping in the observations. PLS-DA was then performed to improve the classification, offer pairwise 227 comparison and search for the variable importance in the projection (VIP) to identify the significantly changed 228 variables induced by CUMS procedure. Dataset acquired from control and model group was applied to conduct a 229 new PLS-DA model as the training set, and that of treated group was then used to validate and test the predictive 230 ability of the model in conjunction with the results of behavioral tests. Variables with VIP values larger than 1.0 231 were considered as statistically significant in this model and they were supposed to be the metabolites which 232 counted most in the discrimination between groups. Furthermore, unpaired Student's t-test was carried out for the 233 normalized data and in general, the variables with VIP value larger than 1.0 and q-value less than 0.05 were 234 deemed to be statistically significant. Those variables were then identified according to their m/z and retention 235 time in the following analysis.

In order to explore whether the level of metabolites could reflect the severity of anhedonia in CUMS model, then we studied the association between the changed metabolome and the result of behavioral test. Compared with OPT and FST, the result of SPT varied within a small range, suggesting it was more stable and accurate and it was widely used in CUMS model as a measurement of depressive state, so we defined SP as the Y variable and the metabolic dataset of training set (control and model group) was set as the X variable in the new PLS-DA model and then the dataset of treated group was put into the model as a test set to further validate the performance of the model. The predictive ability and whether the changed metabolome in the simplified panel could reflect the

243 depressive level had been tested, and a permutation test for that model was conducted to confirm it.

244 3. Results 245 3.1 Behavioral test 246 Following the CUMS procedure, the SP of each rat was shown in Fig.2a. Significantly decreased SP had been 247 observed after three weeks' CUMS procedure. While in the following 4 weeks, the SP of model group turned out a 248 sustained downward trend compared with control group, and for that of treated group, it began to rise gradually 249 and at the final SPT, it achieved statistical significance compared with model group. The OPT had been done twice 250 according to the schedule and the results were displayed in Fig.2b,c. The locomotor activities including rearing 251 frequency and the time spent in the central square were recorded to reflect the status of depression. The rearing 252 frequency of rats in model and treated group was significantly decreased compared with control group, while rats 253 received antidepressant treatment, situation was getting better compared with rats without treatment at week 7 and 254 the results of time spent in the central square turned out similar tendency. Previous researches showed that 255 significant reduction of rearing frequency could indicate decreased exploratory behavior, and the time spent in 256 central sector could reflect the degree of anxiety in rodent^{22, 23}. The immobility time in the FST (Fig.2d.) was 257 obviously increased in model and treated groups compared with control group after CUMS exposure. Moreover 258 there was no statistical difference significant difference (p>0.05) between control and treated group at week 7, and 259 it may indicate that the immobility time in FST was closely related to desperation and could reflect the depressive 260 state to some extent. Therefore, according to the results of behavioral tests, the significant decrease for SP, affected 261 locomotor activities and the longer immobility time in FST demonstrated that depressive-like behaviors 262 impairment of hedonic reactivity and anhedonia did occur which meant the model had been successfully 263 conducted.

CUMS procedure also resulted in a reduction of food consumption and further led to the significant decrease of body weight in model rats compared with control rats, and this situation improved after antidepressive treatment. The body weight of three groups was displayed in supplementary information (S-Fig.1), and the detailed data was presented in S-Table.2.

268 3.2 Metabolomics profiling

Metabolic profiling was conducted according to the chromatographic and mass spectrum conditions described above. To explore the differences between groups, multivariate analysis was performed which help to reduce the data to a low dimensional space where discrimination of metabolomic profiles between sample classes can be modeled. To ensure the stability and repeatability of equipment, the PCA score plots of QC samples were firstly

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273 analyzed to evaluate the general situation of analyzing process. The PCA score plots (S-Fig,2.) indicated that the 274 equipment was stabile during the processing and the reliable data was then used for subsequent multivariate 275 analysis. A total of 4926 (3754 in positive mode and 1172 in negative mode), 4342 (3440 in positive mode and 902 276 in negative mode) and 3813 (2990 in positive mode and 823 in negative mode) features were obtained in the 277 samples of plasma, hippocampus and PFC, respectively. For pre-treated dataset of plasma, a PCA model was 278 achieved which accounted for 47.7% of the total variations in the first three components. Besides, for hippocampus 279 and PFC, 41.2% and 37.8% of the total variations were accumulated within the first three components, respectively. 280 According to the score plots displayed in Fig.3, relative clear separation between control and model group could be 281 obtained which preliminarily indicated metabolic pattern did changed in those samples.

To improve classification, a more sophisticated multivariate model, PLS-DA was performed to maximize discrimination between the three groups. The score plots of PLS-DA model showed a clearly discrimination between groups and the key parameters were displayed in Table.1. Briefly, both R²Y and Q² which were employed to quantify the goodness-of-fit and predictability were greater than 0.5, suggesting that this model was predictive and robust^{24, 25}. According to the score plot, the cluster of treated group was apparently moving towards to that of control group in the first component which was consistent with the results of behavioral tests, suggesting the severity of depression had been improved.

289 3.3 Searching for discriminate variables

The variable importance for projection (VIP) value which signified the influence of variables on the classification was obtained from PLS-DA model. Then the VIP value, along with p-value acquired from the Student's t test was applied for the selection of discriminational variables between three groups. The variables with VIP values larger than 1.0 and p-value less than 0.05 was chosen as the candidate biomarkers and then be identified²⁴.

295 3.4 Metabolite identification

The selected variables which were significantly changed after the CUMS exposure according to VIP-value and p-value were presented in the form of m/z and retention time pairs. Our library had established an in-house library which consisted of 493 authentic chemicals and analyzed in the pre-described conditions with high accurate m/z and retention time. While for those variables without authentic chemicals, the online commercial database including Human Metabolome Database (HMDB version 3.6) and KEGG was searched to putatively identify in the tolerance of 3 ppm according to metabolite identification confidence defined by the Metabolomics Standards Initiative²⁶. The metabolites for both confidently and putatively identified in plasma, hippocampus and PFC

samples were listed in Table.2,3,4, respectively, and the retention time shift of each metabolites with authentic
 chemicals was displayed in S-Table.3,4,5, respectively.

305 However, it was inconvenient and unpractical for diagnosis based on quantification of so many metabolites, 306 so we attempted to search for a simplified metabolite panel in order to represent for the discriminatory power of 307 most metabolites. Moreover, our primary goal is to explore whether there was a temporal relation of metabolome 308 changing from plasma to brain such as hippocampus and PFC, so in this study, we chose the mutual metabolites in 309 plasma, hippocampus and PFC samples. Then in order to explore whether the simplified panel in plasma could 310 correctly reflect the metabolome change in brain, correlation analyses of metabolites in the simplified panel 311 (plasma versus hippocampus and plasma versus PFC) were performed and the plots were displayed in S-Fig.3. The 312 plasma metabolite intensities were correlated with hippocampus metabolite intensities and PFC metabolite 313 intensities, respectively. The scatter diagrams of each metabolites in that panel were displayed in Fig.4, and the 314 calculated Pearson's coefficient values and p-values were shown in Table.5, which indicated a better correlation for 315 panel in plasma with that in hippocampus. Furthermore, we also investigate the correlation between SP and 316 metabolite intensities in the simplified panel to explore the associations of metabolites in simplified panel with 317 disease severity indices and whether the panel could relate the overall metabolome change with the result of 318 behavioral test. The metabolite intensities were mean-scaled to reduce the impact for the difference in the order of 319 magnitude and the results demonstrated that the panel in plasma could basically satisfy the requirement (Fig.5) and 320 the coefficient values and p-values were displayed in Table.6. Specifically, L-kynurenine, quinolinic acid, 321 L-phenylalanine and N-acetyl-L-aspartic acid were negatively associated with the SP (r=-0.70, -0.73, -0.79, -0.74, 322 respectively), indicating that higher level of these compounds in plasma was associated with severer level of 323 melancholic symptoms. Besides, the level of L-tryptophan, gamma-aminobutyric acid and was positively 324 associated with SP which suggested that model rats with more symptoms of anhedonia had lower level of those 325 metabolites in plasma.

In general, according to the Pearson's correlation coefficients, we may draw the conclusion that, the changing tendency of simplified panel in plasma was almost the same as that in hippocampus and PFC which indicated the simplified panel in plasma could partly reflect the changed metabolome in brain. Moreover, we also found the correlation between the normalized dataset of the panel in plasma and SP was relatively good.

The result that whether the simplified could rank the depressive level was displayed in Fig.6. The score plot of the new model conducted by the dataset of training group was shown in Fig.6a which also demonstrated a very clear separation between control and model group. In the predict plot of the new fitted model (Fig.6b), the Y axis

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was the SP acquired from behavioral test, and the X axis was a predicted SP calculated by the model. According to the predict plot, when the test set was put into the new PLS-DA mode, the predicted SP was almost was close to the real SP, indicating that the PLS-DA model was robust and had a relative good predictive power when facing new observations. Furthermore, to rule out nonrandomness of separation, a 50-iteration permutation test (Fig.6c) was performed and the corresponding values from the permutation test were lower than the original value which further validated the model.

339 4. Discussion

340 Nowadays the diagnosis of MDD is mainly rely on symptom-based assessment such as Hamilton depression 341 rating scale (HAMD), in other words the lack of biomarkers which can lucubrate the pathogenesis and further 342 support laboratory-based diagnosis remains a bottleneck in the study and prevention of MDD. In this study, we 343 further explored the metabolome changes in multiple samples in order to find a simplified metabolites panel in 344 plasma which can reflect the metabolome changes in hippocampus and PFC more directly and accurately than our 345 previous urinary metabolomics study. Moreover, we also studied the association between the changed metabolome 346 and the result of behavioral test for the purpose of exploring whether the level of metabolites could reflect the 347 severity of anhedonia in CUMS model. Generally, these results demonstrated that the changed metabolome was 348 able to rate the depressive level in CUMS rats and it was promising and practical to evaluate the severity of MDD 349 by a more objective laboratory-based metabolomics method in conjunction with behavioral tests. Finally, in this 350 study, a UPLC-Orbitrap-MS based metabolomics profiling was conducted to capture the significantly changed 351 metabolites in plasma and brain samples, then the understanding of these metabolites could provide new insights 352 into underlying the pathogenesis and promote the discovery of biomarkers which could be used in the diagnosis or 353 precaution for MDD.

354 4.1 CUMS-induced metabolomic changes

355 After the exposure of CUMS procedure, metabolic changes were observed and the changed metabolome was 356 mainly involved in the amino acids metabolism, lipid metabolism, energy metabolism, oxidative stress and 357 endocrine metabolism shown in Fig.7. According to the mutual metabolites in plasma, hippocampus and PFC, we 358 simplified the changed metabolome into a panel consisting six metabolites. Considering the practicability of the 359 biomarkers in the future research of diagnosis, we placed more emphasis on the biointerpretation of metabolites in 360 the simplified panel along with corticosterone which could connect the changed metabolome between plasma and 361 brain. Moreover, we also gave detailed biochemical interpretation for the remaining significantly-changed 362 metabolites in supplementary information.

363 The significantly changed level of tryptophan (Trp) and its metabolites kynurenine (Kyn), kynurenic acid 364 (KYNA), quinolinic acid (QUIN) and 5-hydroxyindoleacetic acid (5HIAA) was observed after CUMS procedure 365 in model group. Trp was an essential amino acid in our body which acted as the precursor of serotonin. The 366 serotonin was a local transmitter at synapses which acted as the biochemical messenger and regulator in the central 367 nervous system and it had been proved that the significantly decreased level of serotonin had a close relationship 368 with MDD according to the monoamine neurotransmitter hypothesis. In addition to participating in the 369 biosynthesis of proteins, Trp could be catabolized in two main pathways: Kyn pathway and serotonin (5-HT) 370 pathway. For the Kyn pathway, Trp was firstly converted into N'-formylkynurenine by indoleamine-2, 371 3-dioxygenase (IDO) or L-tryptophan-2, 3-dioxygenase (TDO). It had been reported that the increasing 372 proinflammatory cytokines like IL-6 and TNF- α can active IDO²⁷, and then the activation of Kyn pathway would 373 result in that more Trp was then catabolized into formylkynurenine, while for serotonin pathway, the decline of Trp 374 would cause the decrease of its metabolites serotonin. Moreover, even though the serotonin hadn't been detected in 375 this study, the level of its main breakdown product 5-HIAA was significantly decreased which might partly due to 376 the down-regulation of serotonin. Interestingly, according to the results of ELISA (S-Fig.4), the levels of IL-6 and 377 TNF- α was significantly higher in the plasma of model rats and this validated the activation of Kyn pathway and 378 moreover, it also indicated MDD would be an inflammatory disease which offered the chance to have a new 379 understanding of MDD in a new perspective. Additionally, the decreased level of Trp, along with the significantly 380 increased level of Kyn and its catabolite QUIN also demonstrated the metabolism of Trp was mainly converted 381 into Kyn pathway.

382 When the metabolism of Trp was converted into Kyn pathway where the metabolites had appreciable effect 383 on the neuroprotective-neurodegenerative balance in the brain. Kyn could be furthered catabolized by two 384 pathways: the toxic quinolinic pathway where several excitotoxic metabolites were produced and the kynurenic 385 pathway. In quinolinic pathway by the function of kynurenine-3-monoxygenase, Kyn could be catabolized in to 386 3-hydroxy kynurenine (3-HKK) which proved to be an endogenous excitotoxin and the bioprecursor of QUIN. It 387 could generate free radical which was able to cause damage to the function of brain including the apoptosis of 388 neurons or some neurodegenerative changes. For QUIN, it was a kind of NMDA receptor agonist which was 389 produced by microglial cell. And it was associated with several psychiatric and neurodegenerative disorders 390 including Parkinson's disease, MDD and Alzheimer's disease^{28, 29}. It had been reported that cytokines could induce 391 an increase for QUIN in the plasma and cerebrospinal fluid of MDD patients and the significantly evaluation of 392 proinflammatory cytokines in plasma had been observed in CUMS model rats which was consistent with previous

393 studies²⁸. In the condition of nerve inflammation, QUIN could over-activate NMDA receptor and inhibit the 394 resorption of glutamic acid (Glu) for gliocyte which worsen the excitotoxin of Glu in central nervous system. 395 When the level of QUIN gradually increased and reached the pathological level, it could affect the function of 396 neuron or even induce apoptosis. Additionally, QUIN was also able to produce the toxic effects by lipid 397 peroxidation or undermining the stability of neuronal cytoskeleton. Under normal condition, astrocyte could 398 reabsorb the released Glu by synapse, then convert Glu to glutamine (Gln) and finally release Gln to presynaptic 399 membrane in order to regulate the level of Glu. However, the increased level of QUIN was capable to cause a 400 reduction for glutamine synthetase, leading to a turbulence of the regulation for Glu in astrocyte and leading to 401 accumulation of Glu. Glu had been widely accepted as an excitatory neurotransmitter, consisting in all neurons in 402 CNS and the dysregulation or over-activating its receptor would finally had a bad effect on neurons. As was 403 mentioned, the evaluation of QUIN along with the accumulation of Glu would over-activate the NMDA receptor, 404 producing the synergetic effect and intensifying the excitotoxic effect in CNS. Worse still, the decrease for 405 astrocyte led to an increase of proinflammatory cytokines which then further activated the Kyn pathway and 406 resulted in a vicious cycle. Studies had shown that antagonist of metabotropic glutamate receptor1 (mGluR1) and 407 NMDA could alleviate the damage of QUIN³⁰. In the animal model, when received injection of AIDA or MK-801 408 could down-regulation of QUIN and relieve some depressive symptoms³¹. We could deduce that the stress-induced 409 immune response regulation resulted in an increase of proinflammatory cytokines which further led to the 410 activation of Kyn pathway and the evaluated-level of QUIN. Based on this result, we could further look into the 411 association between QUIN and Glu and have a deeper understanding of the mechanism of MDD from a new 412 perspective.

413 Kyn was also be able to be catabolized into KYNA which proved to be a well-known endogenous antagonist 414 of the NMDA receptor and maintained the balance of neuroprotective-neurodegenerative metabolites. However, 415 the pathological level of QUIN which caused the apoptosis of astrocytes as mentioned above, it could lower 416 neuroprotective activity and resulted in the decreased level of KYNA which was observed in our study. The 417 changed balance indicated a metabolic disturbance involved in MDD. In contrast to QUIN, KYNA was a 418 neuroprotective metabolite as a NMDA receptor antagonist which could mediate glutamatergic hypofunction. 419 Studies had focused on it to explore the relationship between its neuromodulatory character and the pathogenesis 420 of several CNS diseases. It had been reported that different patterns of abnormalities in KYNA metabolism was observed in Huntington's disease and Alzheimer's disease^{32, 33}. There was evidence that KYNA was associated with 421 422 cognition and memory for the impairment of cognitive function in various neurodegenerative disorders was

423 accompanied by metabolism alteration of KYNA. Our research indicated a significantly down-regulation of 424 KYNA in model group and in combination with the significantly up-regulation of QUIN, suggesting that the 425 metabolism of Kyn was mainly going into the toxic quinolinic pathway which led to an imbalance in the 426 neuroprotective and neurodegenerative metabolites in CNS.

427 Phenylalanine (Phe) was an essential amino acid which was involved in the synthesis for cellular proteins and 428 it was also the precursor for the amino acid tyrosine (Tyr) because of the similarity in structure. Phe could be 429 firstly metabolized into Tyr by hydroxylation under the function of phenylalanine hydroxylase in liver, then as a 430 precursor for L-dopa, Tyr was able to be further metabolized to several neurotransmitters like dopamine, 431 norepinephrine and epinephrine. It had been reported that MDD patients showed a significantly higher Phe-Tyr 432 than healthy control while under normal circumstances half of Phe was supposed to convert into the biosynthesis 433 of Tyr, suggesting there might be a dysfunction of related enzymes³⁴. The increased level of Phe along with the 434 decreased level of Tyr observed in our research was consistent with former study. Additionally, as a precursor for 435 neurotransmitters, it shared the transport system across the blood-brain barrier with tryptophan. The metabolic 436 alteration of Tyramine, L-dopa and its metabolites dopamine and homovanillic acid (HVA) was also been observed 437 in model rats which demonstrated the turbulence in Tyr metabolism and this was supported by monoamine-based 438 mechanism for MDD. Then due to the metabolic disturbance of Phe and Tyr, in combination of the lower 439 concentration of dopamine and HVA, we speculated the biosynthesis for neurotransmitters in was influenced in the 440 pathogenetic process of MDD. Further study could be conducted by using targeted electrochemistry-based 441 platform to interrogate perturbations in the neurotransmitter pathways involving, dopamine, epinephrine and 442 norepinephrine to discover the association between monoamine neurotransmitters and MDD.

443 Gamma-aminobutyric acid (GABA) proved to be an inhibitory neurotransmitter which acted on inhibitory 444 synapses in CNS. It was involved in the regulation of neurotransmitters for amines, peptides and amino acids by 445 linking with specific receptors for pre or post synaptic neurons. This binding caused the opening of ion channels to 446 allow either the flow of negatively-charged chloride ions into the cell or positively-charged potassium ions out of 447 the cell. This will typically resulted in a negative change in the transmembrane potential, usually causing 448 hyperpolarization. Unlike monoamine neurotransmitter, GABA existed in almost 50% of synapsis and could be 449 metabolized by Glu via glutamate decarboxylase. It had been proved in animal models that GABAergic 450 innervation was able to suppress the secretion of corticotropin releasing hormone (CRH) in paraventricular 451 nucleus³⁵. CRH was a key metabolite in the activation of hypothalamus-Pituitary-adrenal (HPA) axis and the 452 evaluation of CRH could lead to an over-activation of HPA axis which was vital in the pathogenic process of MDD.

453 In CUMS model, a reduction of GABAergic innervation had been observed, sequentially the inhibiting effect of 454 GABA for CRH iminunoreactive neuron, while after injection of CRH antagonist the depressive symptoms 455 improved. Previous studies showed a higher level of Glu in occipital cortex and a lower level of GABA in MDD 456 patients and the level of GABA was in inverse proportion of Glu in the same brain region³⁶. Additionally, drugs 457 which was capable to increase the level of GABA or acted as the agonists of GABA receptors had been reported 458 had anti-anxiety and anti-convulsive effects. A significantly decreased level of GABA might indicate the 459 dysfunction of GABA synthesis and this was partly due to the reduction of glutamatergic stimulation and the 460 aberrant activity of glutamic acid decarboxylase which cause a block for Glu to convert into GABA. Moreover, the 461 lower activity of glutamic acid decarboxylase was observed in MDD patients and even some environmental factors

was also able to have an impact on glutamic acid decarboxylase.

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463 N-Acetylaspartic acid (NAA) was a derivative of aspartic acid by acetylization and it was a high-activity 464 neuropeptide in brain. Its precursor aspartate was derived from TCA cycle and involved in energy production. 465 NAA was the second most concentration compound in the CNS for mammals just next to that of Glu. NAA was 466 biosynthesized in by aspartic acid and acetyl-coA in neuronal mitochondria. It could act as a neuronal osmolyte to 467 maintain the fluid balance in brain and it was also involved in the biosynthesis for lipid and myelin in 468 oligodendrocytes. Additionally, it was also a precursor for the synthesis of the important neuronal dipeptide 469 N-acetylaspartylglutamate. NAA was recognized as a marker for the integrity and viability of neuronal, under 470 normal circumstances, NAA was able to be transferred from neuron to oligodendrocyte and thus to clear the 471 redundant free NAA. Interestingly, the dysregulation of NAA in brain and plasma was not consist with each other 472 in previous studies^{37, 38}. In oligodendrocyte, part of NAA was catabolized and synthesized the fatty acids and 473 steroids. However, when under pathological states, it could induce an increasing release for NAA due to the 474 damage of neuron and the evaluated level was firstly converted into astrocyte and then transferred to the 475 bloodstream. Moreover, astrocyte played an important role in the formation of the blood-brain barrier, and 476 extracellular NAA could be absorbed by astrocyte-expressed transporter. The dysfunction of the reabsorption for 477 NAA could also be responsible for the abnormal level of NAA in plasma, while the decreased levels of NAA in 478 brain might imply the deficits in neuronal activity and the function of mitochondrial. Generally, the increased level 479 of NAA in plasma along with the reduction of that in hippocampus and PFC might partly indicated a dysregulation 480 for NAA and a pathological state in model rats.

481 Corticosterone (CORT) is an adrenocortical steroid that has modest but significant activities as a 482 glucocorticoid. There was a great deal of researches had proved that when exposed to long-tern stressors, the

483 activity of neurosecretory system increased and manifested the hyperfunction for hypothalamic-pituitary-adrenal 484 (HPA) axis which led to an increasing level of glucocorticoid^{39, 40}. A notable evaluation of cortisol had been 485 observed in many studies which focused on concentration of glucocorticoids in the blood of MDD patients. In our 486 study, the level of another kind of glucocorticoid, CORT was significantly increased and it was the main existing 487 form for glucocorticoid in rodents. Moreover, long-term injection of CORT had been proved as another effective 488 method to induce depressive-like action which was widely applied in the development of anti-depressive drugs. 489 Study had showed that after long-term injection of CORT, both the synaptophysin (SYP) which was a marker for 490 plasticity of neuron structure and brain-derived neurotrophic factor (BDNF) were down-regulated which further 491 induced dysfunction of neuron⁴¹. Additionally, cerebral glycogen was responsible for providing energy in neuronal 492 activity and the dysfunction of neuron in early stage was also partly due to metabolic disturbance of energy. SYP 493 was a kind of calcium binding membrane protein which had close relationship with structure and function for 494 synapsis and research indicated that CORT could suppresses the generation of nervous system and then reduce the 495 density for hippocampal dendritic spines which resulted in a dysfunction of the spatial learning and memory. So 496 the increasing level of CORT could be involved in formation and development of synapsis, while the decreased 497 synapsis and diminished function had an effect on the information dissemination in CNS. Besides, glucocorticoid 498 was able to directly influence glycogen metabolism of astrocyte and CORT could cause a notable reduction of 499 glycogen in astrocyte. The decreased concentration of glycogen was associated with the metabolism and function 500 of astrocyte. The deficiency of glycogen in astrocyte might further result in neuron apoptosis which could affect 501 the metabolism of neurotransmitters and the transmission of action potential.

502 Hypothalamic-pituitary-adrenal (HPA) axis played a key role in response to various kinds of stress. When 503 stress signals reached thalamic paraventricular nucleus, it would lead to a secretion for corticotropin releasing 504 hormone (CRH)³⁹. Then the release of CRH would promote the generation of adrenocorticotrophic hormone 505 (ATCH) by anterior pituitary which further promote the release of glucocorticoid in order to cope with stress. 506 Hippocampus was not only a sensitive region for stress-induced damage but also a regulation center for HPA axis. 507 Hippocampus could inhibit the stress reaction and make the over-activated HPA axis return to normal. However, 508 there were abundant receptors of glucocorticoid in hippocampus so it was very sensitive to the level of 509 glucocorticoid while the increasing CORT would cause damage to hippocampal synaptic plasticity. When 510 superfluous glucocorticoid in plasma passed through blood brain barrier and acted on the receptors in brain, 511 degenerative feedback was generated by hippocampus to inhibit the activity of HPA axis to maintain hormonal 512 balance. However, when long-term exposure to high level of glucocorticoid caused an over-activity of

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513 glucocorticoid receptors which further led to a weakening effect for the degenerative feedback. Worse still, the loss 514 of the inhibition effect for HPA axis then secreted more and more glucocorticoid which resulted in a vicious cycle 515 which could be manifested from atrophy of dendrites and neurons to impaired function of emotion and memory.

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518 5. Conclusion

519 In the present work, metabolic changes in plasma, hippocampus and PFC of CUMS rats was investigated by a 520 UPLC-Orbitrap-MS based metabolomics method. The significantly changed metabolome induced by CUMS 521 procedure revealed the disturbance in neuroendocrinology, amino acid metabolism, energy metabolism, lipid 522 metabolism and synthesis of neurotransmitter. According to the common potential biomarkers in three kinds of 523 samples, we simplified the significantly altered metabolites into a panel which was consist of L-tryptophan, 524 L-kynurenine, quinolinic acid, L-phenylalanine, gamma-aminobutyric acid and N-Acetylaspartic acid. The 525 correlation analysis between the simplified panel in plasma and that of brain obtained a relative good results which 526 indicated that the plasma panel was able to reflect the metabolic changes in brain. According to the metabolic 527 pattern acquired by PCA model, we speculated there was a temporal relation for metabolic changes. Specially, 528 when the simulation of CUMS acted on model rats, it could lead to a series of effects on neuroendocrine and 529 metabolic system which caused the metabolome change in peripheral blood firstly for that blood was circulating 530 through the body constantly. Then the changed level of several metabolites was able to further affect hippocampus, 531 inducing functional or organic changes which might result in a vicious cycle. Finally the metabolic disturbance and 532 the dysfunction of hippocampus probably brought about the damage for PFC. Significantly changed metabolites 533 could support this view and we also gave proper biological interpretation for them in order to match it. 534 Additionally, the predictive power between the metabolome and SP achieved satisfactory results which meant it 535 was practicable to reflect the depressive degree by a metabolomics method. Compared with behavioral test, the 536 changed metabolome was more objective and it could minimize the effect of subjective action for animals during 537 the behavioral test. Even if the test of the simplified panel was not as convenient as behavioral, it was promising to 538 replace behavioral tests gradually for its objectivity with the development of detecting technology. We explored the 539 metabolic changes in three kinds of different samples, and furthermore, it was the first attempt to rank the 540 depressive level in CUMS model by a metabolomics approach in order to explore the relationship between 541 metabolome and severity of depression. These results indicate that it is promising to search for biomarkers for 542 diagnosis by metabolomics method through a noninvasive blood sample rather than cerebrospinal fluid or even

543	biopsy of brain tissue. Additionally, this untargeted metabolomics research would deepen the understanding for
544	MDD in animal models and lay foundation to further studies such as targeted metabolomics research or studies
545	based on human beings.
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656	Figure Legends
657	Fig.1 Experimental design for the present study.
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659	Fig.2 The results of behavioral tests for SPT (a), OPT (b,c) and FST (d) of the control, model, and treated group.
660	Data are represented as mean±SD.
661	* means a statistically significant difference at p<0.05, ** means a statistically significant difference p<0.01
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664	Fig.3 The PCA and PLS-DA score plot in plasma (a), hippocampus (b) and PFC (c). The left side is the PCA score
665	plot and the right side is the PLS-DA score plot conducted by the dataset of three groups.
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667	Fig.4 The scatter diagrams of each metabolites in the simplified panel in plasma.
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669	Fig.5 The diagram of linear-regression analysis between SP and the level of metabolites in the simplified panel in
670	plasma.
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672	Fig.6 The plots of newly-conducted predictive PLS-DA model of plasma. The left side is the score plot conducted
673	by the training set (control and model group) $R2X$ (cum)=0.686, R^2Y (cum)=0.994, Q^2 (cum)=0.748; in the middle is the
674	predicted plot from PLS-DA model, the X axis is the predicted SP and the Y axis is the real SP; on the right side is
675	the 50-iteration permutation test, showing that the values of permuted R^2 and Q^2 (bottom left) are significantly
676	lower than the corresponding original R^2 and Q^2 values (top right).
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678	Fig.7 The perturbed metabolic pathways in response to CUMS procedure and treatment of paroxetine.
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Table.1 The parameters for assessing the modeling quality of PLS-DA model in plasma, hippocampus and PFC samples

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		PLS-DA				
	Components	$R^2 X (cum)^a$	$R^2Y(cum)^a$	$Q^2 (cum)^{\rm b}$		
Plasma samples	4	0.441	0.994	0.748		
Hippocampus samples	4	0.397	0.993	0.686		
PFC samples	4	0.353	0.991	0.653		

 $a R^2 X (cum) and b R^2 Y (cum) represent the cumulative Sum of Squares (SS) of all the X's and Y's explained by all extracted components and the term of Squares (SS) of all the X's and Y's explained by all extracted components and the term of Squares (SS) of all the X's and Y's explained by all extracted components and the term of Squares (SS) of all the X's and Y's explained by all extracted components and the term of Squares (SS) of all the X's and Y's explained by all extracted components and the term of Squares (SS) of all the X's explained by all extracted components and the term of Squares (SS) of all the X's explained by all extracted components and the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted components are the term of Squares (SS) of all the X's explained by all extracted$

 $692 \qquad b.Q^2 Y \ (cum) \ is \ an \ estimate \ of \ how \ well \ the \ model \ predicts \ the \ Y's.$

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					Model vs	s. Control	Model v	s. Treat	Corresponding metabolic
No	Metabolite	m/z(amu)	t _R (min)	VIP ^c score	fold change ^d	p-value	fold change ^d	p-value	pathway
1	L-Phenylalanine ^a	165.0785	2.53	1.87	1.55	9.31E-09	1.14	0.019	Synthesis of neurotransmitter
2	Gamma-Aminobutyric acid ^a	103.0631	7.04	2.19	0.49	2.04E-09	0.71	3.22E-04	Synthesis of neurotransmitter
3	L-Tryptophan ^a	204.0901	4.54	1.83	0.54	3.45E-08	0.68	1.90E-04	Tryptophan metabolism
4	Glycine ^a	75.03179	0.91	1.78	0.52	5.23E-08	0.74	0.013	Glycine and serine metabolism
5	Dopamine ^a	153.0785	1.08	1.73	0.50	1.25E-06	0.67	N.S.	Synthesis of neurotransmitter
6	Beta-Alanine ^a	89.04808	6.92	1.77	0.72	1.91E-06	0.83	0.02	Alanine metabolism
7	Azelaic acid ^a	188.1058	1.51	1.77	0.68	2.95E-06	0.87	4.17E-03	Antioxidant
8	Myoinositol ^a	180.0626	0.67	1.69	0.38	3.56E-06	0.81	N.S.	Galactose metabolism
9	Glucose ^a	180.0631	0.65	1.51	0.43	9.63E-06	0.87	N.S.	Energy metabolism
10	L-Kynurenine ^a	208.0844	5.85	1.79	2.27	2.04E-05	1.55	3.84E-03	Tryptophan metabolism
11	Hypoxanthine ^a	136.0392	0.65	1.43	0.47	5.21E-05	0.70	N.S.	Purine metabolism
12	Glycerol ^a	92.04758	0.94	1.70	0.65	9.45E-05	0.87	N.S.	Glycerolipid metabolism
13	Quinolinic acid ^a	167.0213	0.94	1.51	1.75	1.81E-04	1.35	6.15E-03	Tryptophan metabolism
14	Kynurenic acid ^a	187.0276	0.69	1.42	0.53	1.91E-04	0.78	8.25E-03	Tryptophan metabolism
15	N-Acetyl-L-aspartic acid ^a	175.0480	4.28	1.64	1.88	2.12E-04	1.26	5.23 E-03	Synthesis of neurotransmitter
16	Citric acid ^a	192.0261	1.08	1.39	0.76	4.53E-04	0.87	0.015	Energy metabolism
17	PC(14:0) ^b	757.5612	11.10	1.48	1.96	5.31E-04	1.53	0.024	Lipid metabolism
18	LysoPE(20:0) ^b	509.3476	9.59	1.60	1.56	5.51E-04	1.25	5.95 E-03	Lipid metabolism
19	PC(16:0) ^b	807.5751	10.63	1.33	0.60	8.71E-04	1.08	N.S.	Lipid metabolism
20	Sorbitol ^a	182.0788	5.33	1.45	0.67	9.58E-04	0.82	0.011	Galactose metabolism
21	LysoPC(20:5) ^b	541.3153	8.56	1.77	1.46	1.63E-03	0.93	N.S.	Lipid metabolism
22	Corticosterone ^a	346.2146	6.85	1.59	1.36	4.52E-04	1.13	N.S.	Hormone metabolism
23	LysoPC(22:6) ^b	567.3326	8.86	1.51	1.73	3.89E-03	1.40	0.011	Lipid metabolism

Table.2 Potential biomarkers c	haracterized in the p	plasma profile and	their change trends in	n different groups (n =	10 in each group)
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	24	LysoPC(20:4) ^b	543.3318	8.92	1.37	1.29	6.42E-03	1.13	N.S.	Lipid metabolism	
	25	LysoPE(16:0) ^b	453.2844	9.15	1.28	1.35	7.16E-03	1.20	0.010	Lipid metabolism	
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696		a Metabolites identified	by comparing with aut	hentic standa	ards available in	n our in-house	e library.				
697		b Metabolites identified	by comparing with the	HMDB data	abase.						
698		c.Variable importance in	the projection (VIP) v	alues were c	btained from c	ross-validated	PLS-DA mode	ls with a thre	shold of 1.		
699		d. Fold change was calcu	ulated as the ratio of th	e mean meta	bolite levels be	etween two gro	oups.				
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					Model vs. Control		Model vs. Treat		Corresponding metabolic
No	Metabolite	m/z(amu)	t _R (min)	VIP ^c score	fold change ^d	p-value	fold change ^d	p-value	pathway
1	L-Tryptophan ^a	204.0902	4.46	1.97	0.54	3.13E-07	0.76	7.85E-04	Tryptophan metabolism
2	L-Tyrosine ^a	181.0736	1.04	1.93	0.70	6.40E-07	0.83	6.77E-03	Tyrosine biosynthesis
3	Citric acid ^a	192.0266	1.02	1.73	0.69	1.57E-06	0.89	N.S.	Energy metabolism
4	L-Valine ^a	117.0791	5.22	1.63	0.57	4.07E-06	0.79	0.038	Valine and isoleucine biosynth
5	N-Acetyl-L-aspartic acid ^a	175.0482	4.43	1.85	0.55	4.37E-06	0.79	6.63E-03	Synthesis of neurotransmitter
6	Dihydroxyacetone phosphate ^b	169.9974	0.86	1.61	0.63	6.62E-06	0.82	6.79E-03	Glycerolipid metabolism
7	L-Kynurenine ^a	208.0838	5.96	1.76	1.29	8.77E-06	1.17	5.91E-03	Tryptophan metabolism
8	Quinolinic acid ^a	167.0220	0.90	1.47	1.62	5.19E-05	1.29	0.019	Tryptophan metabolism
9	Inosine ^a	268.0806	1.87	1.72	1.40	7.08E-05	1.20	3.59E-03	Inositol phosphate metabolism
10	Glutathione ^a	307.0838	0.98	1.66	1.34	8.89E-05	1.14	3.81E-03	Cysteine metabolism
11	LysoPE(18:0) ^b	481.3168	9.80	1.51	1.48	9.94E-05	1.08	0.410	Lipid metabolism
12	LysoPC(16:0) ^b	495.3325	9.20	1.48	1.33	1.52E-04	1.15	0.031	Lipid metabolism
13	3-Hydroxy-hexadecanoic acid ^a	272.2360	5.07	1.65	0.53	3.40E-04	0.74	7.37E-03	Lipid metabolism
14	L-Isoleucine ^a	131.0949	1.23	1.44	0.51	3.90E-04	0.66	9.77E-03	Valine and isoleucine biosynt
15	L-Phenylalanine ^a	165.0785	2.50	1.68	1.65	5.68E-04	1.40	2.45E-03	Synthesis of neurotransmitter
16	Myoinositol ^a	180.0623	0.62	1.46	1.26	7.41E-04	1.06	0.045	Inositol phosphate metabolisn
17	Gamma-Aminobutyric acid ^a	103.0635	6.90	1.58	0.81	9.32E-04	0.92	N.S.	Synthesis of neurotransmitter
18	Glycerol ^a	92.0474	0.92	1.27	0.70	9.42E-04	0.87	N.S.	Glycerolipid metabolism
19	L-Serine ^a	105.0427	1.72	1.53	0.63	1.43E-03	0.78	0.013	Glycine and serine metabolisr
20	LysoPE(16:0) ^b	453.2854	9.10	1.40	1.34	2.22E-03	1.08	N.S.	Lipid metabolism
21	Homocysteine ^a	135.0357	1.98	1.58	1.19	5.43E-03	1.07	N.S.	Cysteine metabolism
22	Succinic acid ^a	118.0273	1.42	1.35	0.55	5.69E-03	0.79	0.024	Energy metabolism
23	Beta-Alanine ^a	89.0481	7.01	1.28	1.31	7.03E-03	1.07	N.S.	Alanine metabolism

Table.3 Potential biomarkers	s characterized in the hippocar	npus profile and their change tren	ids in different groups ($n = 10$)	in each group)
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713	a Metabolites identified by comparing with authentic standards available in our in-house library.
714	b Metabolites identified by comparing with the HMDB database.
715	c.Variable importance in the projection (VIP) values were obtained from cross-validated PLS-DA models with a threshold of 1.
716	d. Fold change was calculated as the ratio of the mean metabolite levels between two groups.
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					Model vs. Control		Model vs. Treat		Corresponding metabolic		
No	Metabolite	m/z(amu)	t _R (min)	VIP ^c score	fold change ^d	p-value	fold change ^d	p-value	pathway		
1	Kynurenic acid ^a	189.0428	0.73	1.93	0.53	1.14E-06	0.70	7.21E-04	Tryptophan metabolism		
2	L-Tryptophan ^a	204.0897	4.46	1.88	0.73	1.45E-05	0.82	3.77E-03	Tryptophan metabolism		
3	Dopamine ^a	153.0787	0.96	1.82	0.67	1.24E-04	0.80	8.33E-03	Synthesis of neurotransmitter		
4	Quinolinic acid ^a	167.0210	0.99	1.84	1.56	1.35E-04	1.25	2.51E-03	Tryptophan metabolism		
6	Inosine ^a	268.0806	1.90	1.80	1.66	1.48E-04	1.12	N.S.	Inositol phosphate metabolism		
7	Linolenic acid ^a	278.2240	8.99	1.54	1.16	1.56E-04	1.07	N.S.	Alpha-Linolenic acid metabolism		
8	L-Dopa ^a	197.0683	0.75	1.78	0.72	5.01E-04	0.87	0.021	Synthesis of neurotransmitter		
9	5-Hydroxyindoleacetic acid ^a	191.0588	0.81	1.71	0.59	5.42E-04	0.72	2.36E-03	Tryptophan metabolism		
10	N-Acetyl-L-aspartic acid ^a	175.0478	4.45	1.80	0.66	8.41E-04	0.78	0.031	Synthesis of neurotransmitter		
11	Docosahexaenoic acid ^a	328.23906	5.78	1.52	0.80	1.27E-03	0.92	0.039	Lipid metabolism		
12	L-Isoleucine ^a	131.0948	1.24	1.57	0.61	1.34E-03	0.76	8.79E-03	Leucine and isoleucine biosynthesis		
13	Gamma-Aminobutyric acid ^a	103.0638	7.09	1.48	0.71	1.89E-03	0.86	N.S.	Synthesis of neurotransmitter		
14	Homovanillic acid ^a	182.0583	0.68	1.61	0.68	2.64E-03	0.85	N.S.	Tyrosine metabolism		
15	L-Kynurenine ^a	208.0846	5.98	1.55	1.39	3.54E-03	1.18	0.033	Tryptophan metabolism		
16	L-Phenylalanine ^a	165.0789	2.52	1.57	1.41	5.40E-03	1.15	0.015	Synthesis of neurotransmitter		
17	L-Lysine ^a	146.1069	5.27	1.74	2.39	6.38E-03	1.72	0.010	Biotin Metabolism		
18	Tyramine ^a	137.0840	9.65	1.37	1.28	8.37E-03	1.18	0.048	Tyrosine metabolism		
19	L-Tyrosine ^a	181.0738	1.05	1.32	0.60	0.011	0.71	N.S.	Tyrosine metabolism		
20	L-Aspartic acid ^a	133.0366	1.14	1.25	1.53	0.016	1.07	N.S.	Alanine metabolism		

Table.4 Potential biomarkers characterized in the PFC	profile and their change trends in different	2 roups (n = 10 in each group)
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733 a Metabolites identified by comparing with authentic standards available in our in-house library.

734 b Metabolites identified by comparing with the HMDB database.

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c.Variable importance in the projection (VIP) values were obtained from cross-validated PLS-DA models with a threshold of 1. 735

736 d. Fold change was calculated as the ratio of the mean metabolite levels between two groups.

		nppocampus	Plasilla V.S. FFC	
Metabolite	r	p-value	r	p-valu
L-Tryptophan	0.8143	p<0.001	0.7089	p<0.00
L-Kynurenine	0.6491	P=0.002	0.6145	p=0.00
Quinolinic acid	0.6674	P=0.001	0.6122	P=0.00
L-Phenylalanine	0.8102	p<0.001	0.5788	P=0.00
Gamma-Aminobutyric acid	0.8593	p<0.001	0.7157	p<0.00
N-Acetyl-L-aspartic acid	-0.6613	p=0.006	-0.5983	P=0.00

Table.6 Pearson's coefficient values and p-values obtained from the binary logistic regression

	Plasma vs. Sucrose Preference				
Metabolite	r	p-value			
L-Tryptophan	0.8187	p<0.001			
L-Kynurenine	-0.6969	p=0.002			
Quinolinic acid	-0.7298	p=0.002			
L-Phenylalanine	-0.7898	p<0.001			
Gamma-Aminobutyric acid	0.7910	p<0.001			
N-Acetyl-L-aspartic acid	-0.7421	p=0.001			



63x22mm (600 x 600 DPI)



133x100mm (600 x 600 DPI)



119x173mm (600 x 600 DPI)



97x53mm (600 x 600 DPI)



69x27mm (600 x 600 DPI)



60x20mm (600 x 600 DPI)



114x73mm (600 x 600 DPI)



Graphic abstract