

1 Hidden Transcriptome Signature in 2 Autism Spectrum Disorder (ASD) is 3 Attributed to the Interpatient 4 Heterogeneity

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10

11 **Abstract** Recent studies of ASD have mostly supported the existence of heterogeneity and
12 genomic variation in ASD which have hindered and restrained development of any effective and
13 targetable treatment for a long time. As numerous studies have shown, both genetic and
14 phenotypic heterogeneity is presented in ASD, however, heterogeneity in genetic level is not fully
15 understood which is the key challenges for the further research. Even dozens of ASD
16 susceptibility genes have been discovered which is commonly accounting for 10 to 20 percent of
17 ASD cases, the internal complex combination of mutated genes that determine the epigenetic
18 factors of ASD is still not comprehensively recognized by the recent studies. First by discouraging
19 the traditional method that have been applied in most of the current research of diseases, this
20 research will then focus on dissecting the heterogeneity of polygenic diseases and analyzing with
21 an unconventional approach for acquiring Differently Expressed Genes (DEGs) in Gupta's Dataset
22 that provided transcriptome of frontal cortex of ASD patients. Divide categories by using
23 unsupervised learning strategy, the results yielded by analyzing within clusters of ASD have
24 supported the feasibility of the attempts to use heterogeneity to reveal its underlying mechanism.
25 This study puts forward the inference that the heterogeneity of polygenic diseases will obscure
26 the molecular signals related to the disease, and at the same time attempts to use heterogeneity
27 to reveal the underlying mechanism.

28

29 **Introduction**

30 Autism Spectrum Disorder (ASD) is referred as a heterogeneous neurodevelopment disorder char-
31 acterized by a series of behavioral and physiological symptoms that mainly diagnosed by the im-
32 pairments in three key facets: language acquisition and verbal expression, social interaction, and
33 range of interests (Tordjman, 2012). About 1 out of 54 children has been identified with autism
34 spectrum disorder (ASD) according to estimates from CDC's Autism and Developmental Disabili-
35 ties Monitoring (ADDM) Network. The heritability of ASD has been studied in a lot of research, but
36 all these findings can only illustrate less than 20% genetic mechanism (El-Fishawy et al., 2010), and
37 we still need to invest a lot of exploration.

38 There is a high level of variation between individuals diagnosed with autism. The phenotypic
39 heterogeneity of ASD is noticeable at every aspects, ranging from the profile to the severity of

40 sensory features—the various range of sensory symptoms in individuals ASD patients that can en-
41 compass hyper-responsiveness, hypo-responsiveness, and unusual sensory interest (*Al-Sadi et al.,*
42 *2015; Schauder and Bennetto, 2016*). As numerous studies have shown, both genetic and pheno-
43 typic heterogeneity is presented in ASD, indicating the high level of variation between each patient
44 diagnosed with autism. However, heterogeneity typically in genetic level is not fully understood,
45 which also brings complexity to the research.

46 Genome-wide investigations support a complex genetic architecture based on major genes and
47 polygenic factors having different extent of contribution across the ASD spectrum. Several etiolog-
48 ical hypotheses for ASD exist, as for example altered synaptic dysfunction leading to an imbalance
49 of excitatory and inhibitory neurotransmission, although a unifying etiological theory is still miss-
50 ing. Abnormalities in brain tissue at the molecular level, including transcriptional and splicing dys-
51 regulations, have been shown to correlate with neuronal dysfunctions. A recent meta-analysis of
52 blood-based transcriptome investigations in ASD remarks the hypothesis of1 implication of the
53 immunologic function(*Tylee et al., 2017*).

54 Comparing to the phenotypic heterogeneity, genetically heterogeneous difference is more likely
55 to worth an insight as it will set forth a preciser investigation and deduction in regards of the eti-
56 ology and pathophysiology of ASD. Currently, genetic etiology is not comprehensively recognized.
57 In the past decade, dozens of ASD susceptibility genes have been discovered which is commonly
58 accounting for 10 to 20 percent of ASD cases in which the de novo and heritable Copy numbervaria-
59 tions (CNVs) are the two that mainly being identified as they accounts for about 10% of randomly-
60 occurred ASD. A variety of genomic analyzing methods adequately demonstrated that the distur-
61 bance of core biological pathways (BP) are predominantly related to other relevant neurodevelop-
62 ment abnormalities. Plenty evidences for converged molecular pathways are suggested in many
63 current studies that other than convergent brain pathways, there are also a significant conver-
64 gence to the extent of molecular mechanisms of ASD (*Geschwind, 2008; Karthik et al., 2014*). Even
65 through the emergence of the considerable genetic heterogeneity that supported by dozen genetic
66 linkage studies, it has often resulted in identification of non-overlapping interested areas and lead
67 to failures for formally replication of autism linkage discovery about the genome-wide understand-
68 ing(*Dao et al., 2017*).

69 The investigations on post-mortem tissue from ASD patients have shed light on the molecular
70 mechanisms underlying the disorder at brain level, confirming the importance of transcriptional
71 analysis in disease characterization. However, the search for a reliable molecular signature for ASD
72 based on peripheral samples, which might help clinicians in early diagnosis and in the identification
73 of ASD subgroups, is still ongoing. Several attempts in this direction have been performed by gene
74 expression analysis of lymphoblastoid cell lines. Overall, these studies suggest the implication of
75 several signaling pathways and the immune response in ASD, but a consistent set of diagnostic
76 biomarkers remains elusive.

77 In neurodevelopment disorders, causality of multiple mutations in general transcription fac-
78 tors gives rise that changes in the general quantity of gene expression regulation may associate
79 with disease risk in random cases of autism. By assessing alternation in the net distribution of
80 gene expression, the premise in the above statement can be tested (*Masi et al., 2017*). Hence, the
81 fundamental challenge needed to be overcome in making progress in investigation of treatments
82 for ASD is the heterogeneity, ranging from determining the hidden heritable genetic information of
83 ASD and dissecting the epigenetic factors more thoroughly in individuals to attempting to converge
84 different possibility of the combined expression of genetic forms of ASD to obtain a controllable
85 set of targetable metabolism pathways for the treatment (*Meltzer and Van de Water, 2017*). That
86 is why any significant progress in the effective treatments of ASD are hindered and refrained. Re-
87 search shown that there are more than 100 gene mutations associated with autism with a high risk
88 in which every single mutation partaking for only a minor selection of cases.

89 Accordingly, there was significant heterogeneity in all aspects of ASD, including onset time,
90 course of disease, symptoms, and developmental outcomes (*Van Gent et al., 1997*). Most investiga-

91 tions on heterogeneity of ASD is grounded on the observation of phenotypic behaviors of patients
92 in which 10 subtypes are mostly well-established based on clinical behavioral presentation of the
93 disorder.

94 Secondly, most of the recent studies on RNA-Seq of ASD patients are based on the assumption
95 of gross similarities between controls and patients, which clustering all ASD patients as a group
96 which supposition of no genetic heterogeneity presented in between ASD patients. To be spe-
97 cific, the first attempting of my research is using statistics from GEO Dataset 'GSE25507' (**Masi**
98 *et al., 2017*) in which more than 47,000 RNA transcriptome profiled by microarrays were purified
99 from peripheral blood lymphocytes with autism ($N = 82$) and controls ($N = 64$). While analyz-
100 ing this dataset, the results—obtained by the cell deconvolution method which is performed by
101 WGCNA—turn out to be unsatisfying: signals of any differential expression genes are manifestly
102 low. Clearly, the genetic complexity and heterogeneity should be taken into account in respects
103 with determining the differential expression genes of ASD for uncovering of the etiological mecha-
104 nisms of ASD. Therefore, the conventional approach of using statistics of controls and ASD patients
105 for any inquisition in conducting research is seemingly inappropriate as for its fine-grained signal
106 and value due to the significant heterogeneity of ASD.

107 Reflecting from the above substantiation of current research, my research will be viewing from
108 a different direction based on the internal structure of the transcriptome profiles. ASD relative
109 frontal cortex samples were divide categories by unsupervised learning strategy, according to the
110 heterogeneity of the data. Through a new perspective, some well-known autism-related genes that
111 hidden in previous transcriptome-based study, like *PAX6*, *GLI2*, *HFE*, *AHI1*, *OXTR*, *CACNA1G* can also
112 be well revealed.

113 **Results**

114 To further support the existence of heterogeneity of ASD that hinder the progress of research and
115 is unfitting for the traditional way, three frontal cortex tissue transcriptomes are collected from
116 published research. Two micro-array datasets (GSE28475 & GSE28521) and one RNA-sequencing
117 dataset (Gupta's) are downloaded and preprocessed by a consistent cutoff (see Method).

118 **Autism-relative signatures are hidden in conventional study.**

119 Pairwise correction analysis shown that the quality of each dataset is relatively high (Figure 1), and
120 the samples are comparable. The Pearson's R correlations between all samples combinations are
121 greater than 0.7. Samples were clustered by their similarity and visualized by dendrogram, and
122 each sample was label by the diagnosis information, autism samples or control samples. Autism
123 and control samples are not well separated in the three datasets (**Figure 1A-C**). This indicate that
124 the overall feature of the transcriptome fail to reflect the difference between patients and normal
125 people. Therefore, we need to compare the autism group with the control group locally, that is, to
126 compare transcriptome profile gene by gene. Analytical strategies based on statistical models are
127 often used to discover the differentially expressed genes (DEGs) between two sets of samples.

128 Thus, these three data were used respectively to find the DEGs by comparing between autism
129 and control, and the genes that differ significantly, with a p-value ranked in the top 1000, were
130 taken out. Only 82 genes have been observed in more than two studies, and only 2 genes have
131 been observed in more than three studies. (**Figure 1D**) The fraction of overlapped genes are lower
132 than the null hypotheses, a random sampling process. Even though previous studies have found a
133 tiny fraction of DEGs related to autism, to some extent, most of these genes are not universal and
134 general and fail to reflect the characteristics of autism. Finally, it's supported that the conclusion
135 drawn by the previous studies may be skewed by the noisy signal, whereas the real transcriptome
136 signature of autism still remains hidden and also explain why researches frequently yielded results
137 in identification of non-overlapping interested areas.

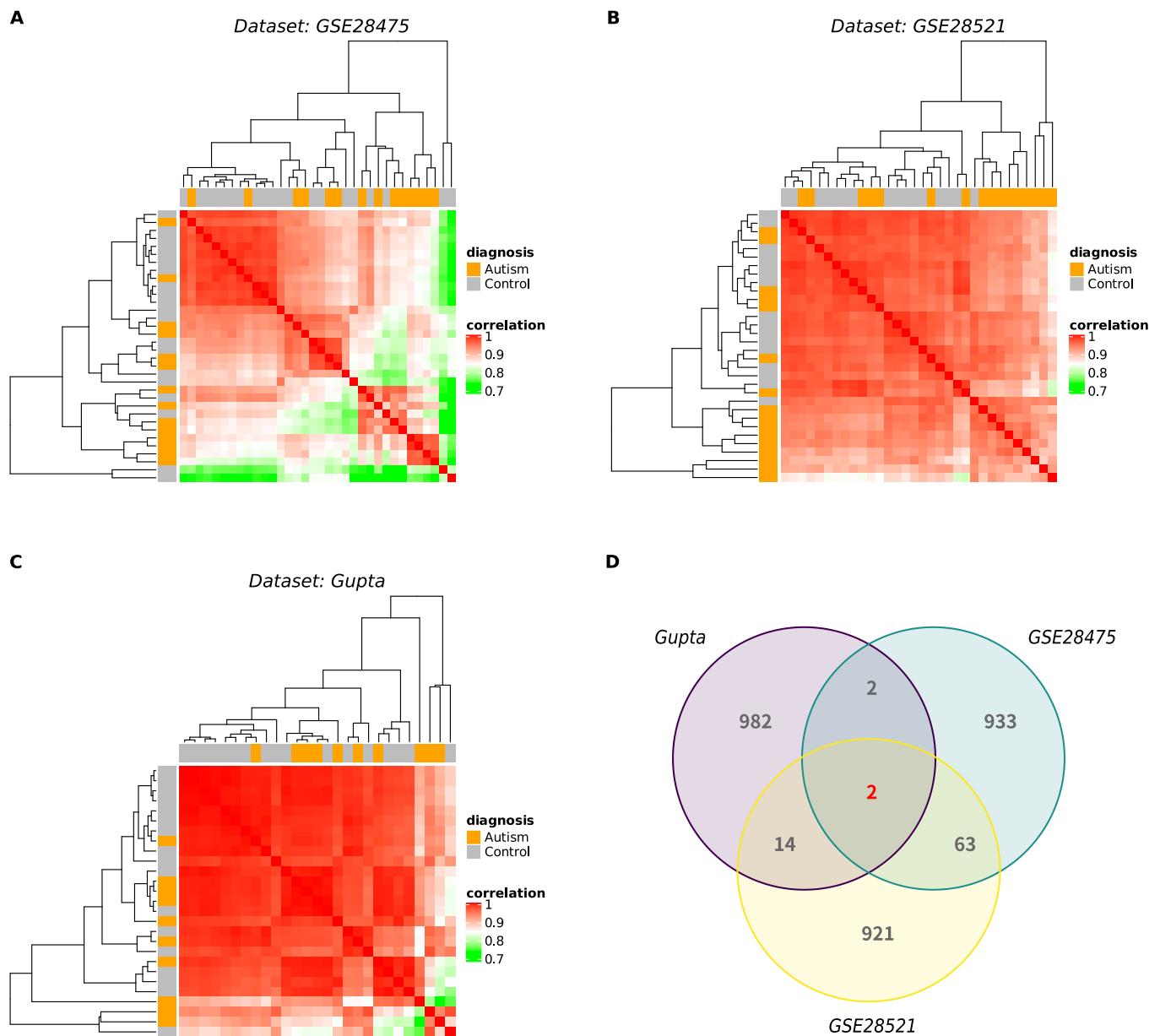


Figure 1. The difference between autism patient and control group in the transcriptome cannot be distinguished by conventional analysis. Heatmap in panel **A**, **B** and **C** are showing the pairwise correlation between every two samples in Dataset GSE28475, GSE28521 and Gupta respectively. Autism and control samples are labelled orange and grey respectively. The dendrogram is representing the similarity among the samples. **D**) The numbers of overlapping DEGs among three datasets are shown in Venn's Diagram.

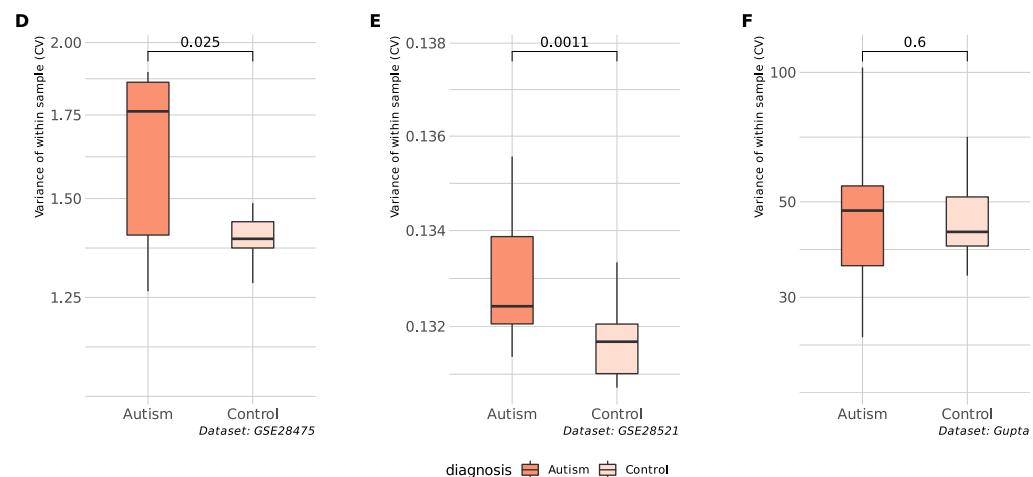
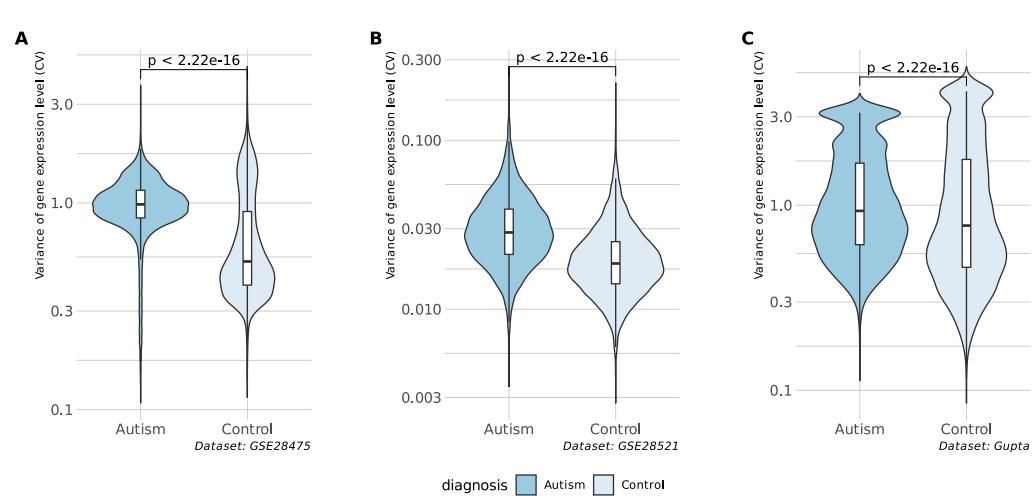


Figure 2. The heterogeneity of samples are measured by Coefficient of Variation (CV). The expression data are categorized by diagnosis types. **A-C.** The variance in the expression level among different samples for each gene is shown by violin plot. **D-F.** The variance in the expression level among different genes for each sample is shown by box plot. The p-value is annotated on each panel.

138 The heterogeneity among autism cases is considerable.

139 To explain why the transcriptome cannot reflect a common characteristics of autism cases, and
140 why the results of previous studies are so different, we speculate that the autism cases are very
141 heterogeneous. The heterogeneity of biological samples is already a widely accepted concept in
142 tumor research, but it is still well considered in the research of autism

143 The coefficient of variation (CV) is used as a measure of the heterogeneity. The usage of CV in
144 instead of variance is due to the immense differences in expression levels among genes, and CV was
145 the variation after correction of the mean value, therefore, CV could provide a better and thorough
146 expression about the data. Firstly, transcriptome profiles are split into autism group and control
147 group. Then, both CV among samples and CV among genes were calculated. CV among samples
148 for each gene (**Figure 2A-C**) indicate from a local perspective, that some genes have indeed under-
149 gone dysregulation. The p-values are all less than 2.22×10^{-16} . CV among genes for each sample
150 (**Figure 2D-F**) indicate from a global perspective, that autism-related transcriptome are deviated
151 from the normal state. These results imply that heterogeneity cannot be ignored in autism study.

152 **Heterogeneous genes are associate with autism signature.**

153 Autism is a multiple gene disease, and each gene basically only contributes a small part of the phe-
154 notype, and the abnormalities of some genes are not enough to trigger the occurrence of disease.
155 Thus, comparison between autism case with control group is not sufficient to reveal all the disease
156 relative signatures in case of small dataset(**Figure 3A**).

157 The transcriptome profiles can be viewed from a different direction based on unsupervised
158 clustering strategy. ASD relative frontal cortex samples were divide categories according to the
159 heterogeneity of the data. Of the three datasets, we choose Gupta's dataset which is based one
160 RNA-sequencing method, and the quality is higher than another two datasets that based on micro-
161 array method. Looking into details about Gupta's dataset, firstly, to reduce dimensions in datasets
162 that close to its intrinsic dimension and produce a new readable visual dataset with lesser num-
163 ber of dimensions, I applied Principal Component Analysis (PCA) with technique tsne, spaced into
164 dataset of autism group of Gupta's dataset into two-dimensional (fig. 3B,C). Verifying with two
165 clustering techniques (kmeans clustering, hierarchical clustering), two clusters of autism samples
166 have clearly demonstrated, differentiating by color blue and orange which respectively represent
167 Cluster 1 and Cluster 2. Indicating from the two clusters shown in transcriptome of brain tissue
168 cortex autism samples of Gupta's dataset, the genetic heterogeneity of ASD was supported and
169 been introducing in this dataset. The running of unsupervised learning method into cluster anal-
170 ysis, helped this exploratory data analysis better in finding hidden patterns or grouping in data
171 accurately and precisely.

172 Arranging the two clusters discovered into two groups for further analysis, the database was
173 utilized to attain the DEGs within two subgroups of autism. By plotting the volcano plot (**Figure 4A**),
174 164 down-regulated and 640 up-regulated gene are found. Enriching the found DEGs on their re-
175 spective pathway by GO and KEGG enrichment (**Figure 4B,C**), these DEGs can enriched in pathways
176 and function module that relate to immune system, epidermal cell differentiation, visual percep-
177 tion and sensory perception of light stimulus (**Dakin and Firth, 2005; Milne et al., 2009; Kikkawa**
178 **et al., 2019; Moreno et al., 2014**). All the term have been reported to be closely related to the
179 emergence of autism.

180 **Hidden autism signatures can be revealed by heterogeneity-based clustering.**

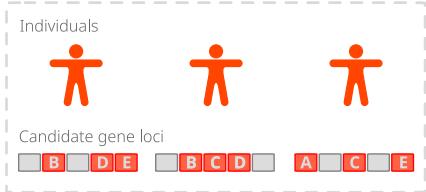
181 Some well-known autism-related genes that hidden in previous transcriptome-based study, like
182 *PAX6*, *GLI2*, *HFE*, *AHI1*, *OXTR*, *CACNA1G* can also be well revealed (**Figure 5**). Manipulating these six
183 DEGs found within Clusters 1 and 2 of autism, we map these genes on the box plot but compare
184 between autism and control. Not surprisingly, all of the six genes shown no significant difference
185 in expression between autism and controls.

186 For example, *PAX6* has an essential role in formation of tissues and organ in embryonic stage
187 of development and expressed in regions like the olfactory bulbs, epithalamus, the ventral thala-
188 mus, striatum and amygdaloid complex during developing phrase of brain that controls brain and
189 nervous tissue development and gliogenesis. *PAX6* was also discovered for a new function as a
190 chromatin modulator that changes the chromatin position of ASD genes in which lead to various
191 phenotypes of ASD and other relative neurodevelopmental disorders. (**Umeda et al., 2010; Scott**
192 **and Deneris, 2005; Gebril and Meguid, 2011**). *GLI2* is one of the subclass of the *GLI* family zinc fin-
193 ger 2 which regards as a strong oncogenes in the embryonal carcinoma cell, having an important
194 function when embryogenesis takes place (**Valente et al., 2006**). *HFE* gene besides discovered on
195 the surface of intentional and liver cells, but also on immune system cells (**Wu et al., 2005**). *AHI1*
196 is a gene regulates the function of cerebellar and other parts of the brain. It is reported to lead
197 to Joubert, a inherited disease of brain development (**Strom et al., 2010**). *OXTR* is a well studied
198 gene which related to autism. Large amounts of research has supported that *OXTR* regulates the
199 behavior of social recognition (**Coutelier et al., 2015**). *CACNA1G* is a T-type Cav3.1 regulation gene,
200 related to development from fetal to human brain (**Careaga et al., 2010; Ritchie et al., 2015a**).

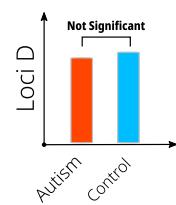
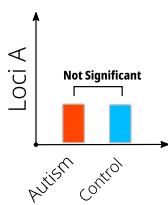
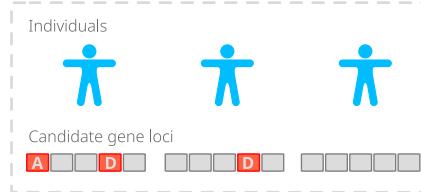
201 As can be seen from the above listing of the functions of the found six DEGs, there is conspic-

A

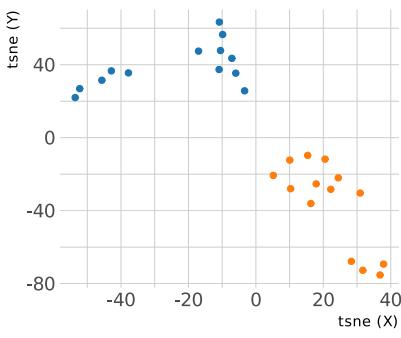
Autism group



Control group



B



C

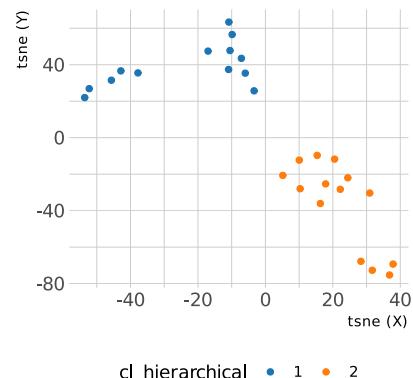


Figure 3. t-SNE clustering reveals heterogeneity in transcriptome profiles of prefrontal cortex. (A) Diagram illustrated the complexity in study polygenic diseases. **(B)** k-means clustering of the expression profile in which each dot represents a single individual. Upset plot for the number of scarring paths detected within or between cell types from the mesoderm. The color code for cell types is as annotated in *Figure 1E*. The yellow shade represents multipotent stem cells. **(C)** Same as panel B, but hierarchical clustering is used instead.

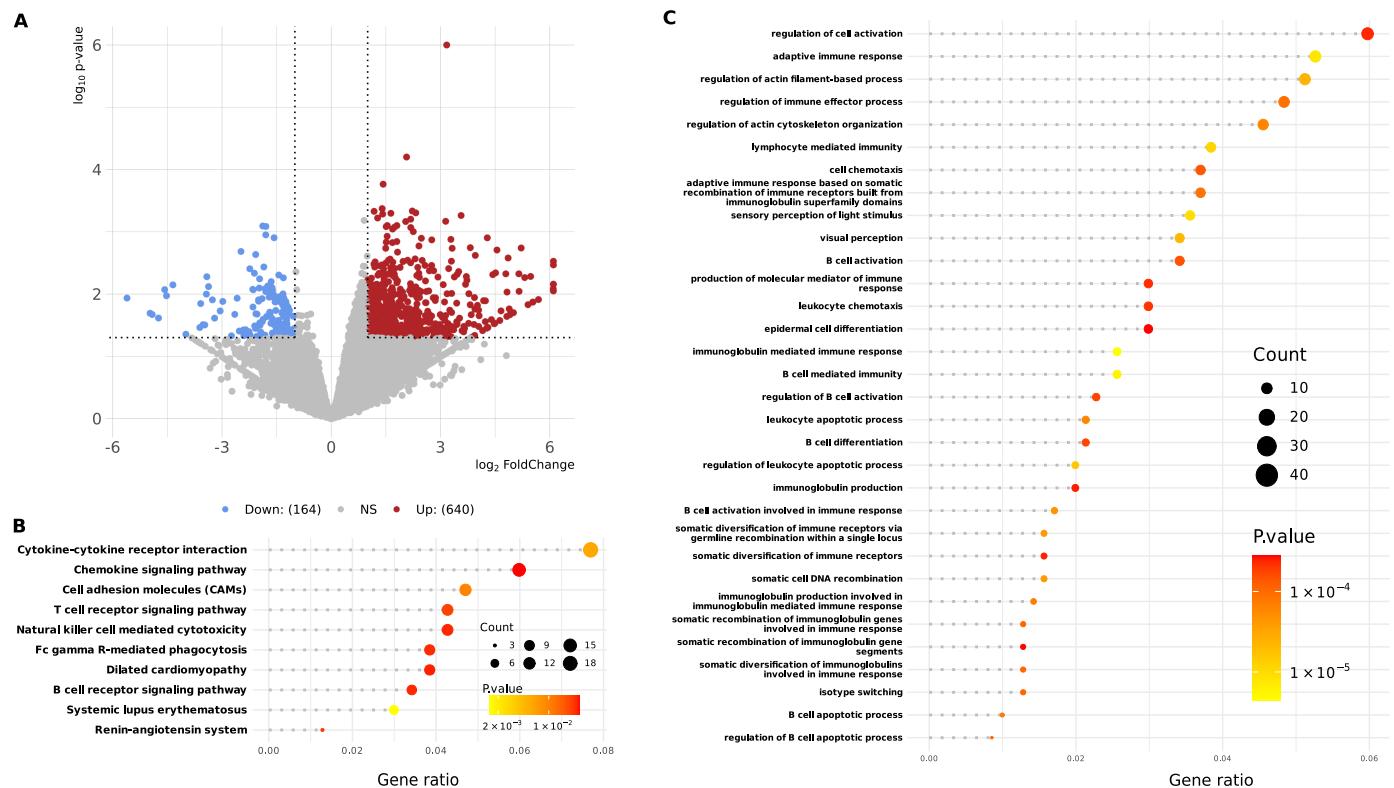


Figure 4. Differential expressed genes between clusters point to functions related to autism. (A)

Volcano plot for DEGs from Gupta's dataset in which the Fold Change and p-value of each gene are shown. The significant up-regulated and down-regulated genes are colored by red and blue respectively. **(B)** KEGG Pathway enriched terms are listed in which the gene count is represented by size of dots and level of significance is represented by color. **(C)** Same as panelB, but GO enrichment analysis is used instead.

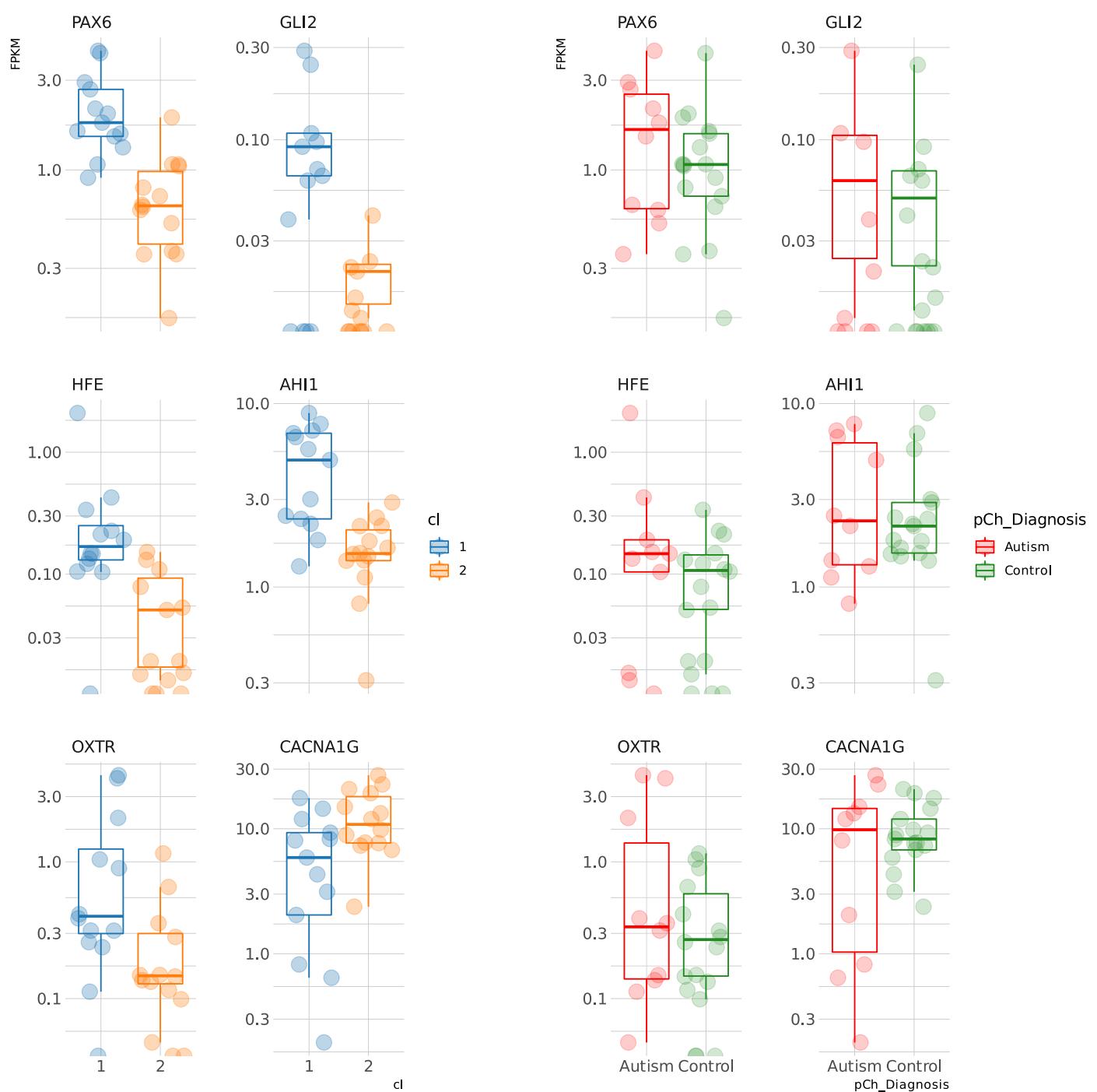


Figure 5. Autism relative genes are significantly different between clusters. The expression level of six well-known autism-related genes, *PAX6*, *GLI2*, *HFE*, *AHI1*, *OXTR*, *CACNA1G*, is shown by box plot. The bold line in the box plot represents the median of the expression level. Each dot represents a biological replication. Expression data on the left side panel is categorized by clusters type whereas on the right panel is categorized by diagnosis.

202 uous finding in common for almost all of the DEGs which their collective correlation with early
203 and embryonic development, especially early development of innate immune system which some
204 studies have recognized *Gu et al. (2016)*. Seen the aspects of early and embryonic development,
205 current research did not have much effort been made, but it's worth a deeper insight into other
206 facet of embryonic development, other than immune system.

207 Discussion

208 A variation of complex genetic and non-genetic aspects partake in the etiology of ASD. Concluding
209 from the result yielded from above analysis, the characteristics of ASD as a polygenic diseases that
210 caused by its internal complex combination of etiology is vastly substantial. For certain combina-
211 tions of specific risk genes, if they are dysregulated at the same time, it can lead to autism. In the
212 case of a small sample size, each individual may have its own pattern.

213 As can be evidently demonstrated, the variation within ASD is relatively high, and the patho-
214 genesis of ASD patients is diverse. To be specific, the abnormality in regulation of one gene may
215 not likely to affect the expression of symptoms of ASD, even if the gene is confirmed to have cor-
216 relation with ASD. Therefore, it can be reasonably interpreted that the etiology is polygenic which
217 a certain combination of gene dysregulation become a causative factors will result in a particular
218 symptoms or subtypes of ASD.

219 To support the statement that heterogeneity of polygenic diseases complicate the molecular
220 signals related to the disease, the sketch map (Fig.3 A) is plotted that simulate the high-risk mutated
221 gene which is labels with letters in the red boxes. Normally, the procedure of conventional studies
222 will first cluster the groups by controls and autism, followed by calculating the difference in gene
223 expression index for tracking down potential the DEGs. However, as the heterogeneity of polygenic
224 diseases is presented, each of the mutated gene is only accounting for a small fraction of cases.
225 Although Gene loci D is a high-risk ASD related gene, shown in Fig.3 A, the only mutation of loci
226 D will not affect the individual to become autistic, indicating by the second members of control
227 group. Due to the polygenic characteristics of ASD, only by jointly mutating of ASD related gene
228 at particular amount, the phenotypic traits of ASD will then expressed. Reasonably inferred from
229 the explanation, in certain dataset, there is no significant difference in frequencies of abnormal
230 expression of loci D. Therefore, by using the conventional differential genes expression analysis,
231 it is unlikely that Loci D is correctly determined and identified on transcriptome level because of
232 singular mutation of one gene is inadequate for resulting in ASD. Due to the polygenic network of
233 ASD, the genes are deciding the phenotypic expression in different ways for different individuals.
234 Therefore, we can successfully reach the verification of the hypothesis — without the occurrence of
235 dysregulation of particular auxiliary gene, the symptoms may not be manifested even if the people
236 is carrying one of the gene that is confirmed to code for ASD.

237 Moreover, as can be inferred from the great variation of ASD, there is a random deviation of
238 trajectory for ASD patients whereas there will be only one trajectory for the normals, leading to
239 the genetic heterogeneity of ASD. This is very similar to the tumorigenesis, which are caused by
240 deviations from the normal developmental trajectory, and there are many types of errors. At the
241 same time, the types of errors can be diverse. On the other hand, genes with high heterogeneity
242 may also be key nodes involved in the gene network of autism. By locating more heterogeneous
243 gene, such as PAX6, GLI2, OXTR, etc., we can understand the whole picture of of autism facilitated
244 by network analysis. This provides effective way for studying of complex diseases in-depth.

245 Hence, this research not only supports the genetic heterogeneity of ASD, but also discover an
246 unconventional approach to overcome the variation of ASD which conducive for the breakthrough
247 of studies of transcriptomes of ASD between by substantiating its high comparability within ASD
248 itself.

249 Methods and Materials

250 Data acquisition.

251 This research exploit three publicly available datasets from previous studies that were retrieved
252 from public repositories.

253 Gupta's dataset:

254 The frozen brain samples obtained through the Autism Tissue Program were dissected and used
255 for RNA library construction and high throughput sequencing. Constructed library were sequenced
256 by Illumina HiSeq-2000 platform. Afterwards, the reads were mapped to human reference genome
257 (version GRCh37), and expression level of each gene was quantified by read counts. Manifold
258 cortical tissues are included in this dataset, but only the frontal cortex samples were selected to
259 minimize between tissue variability and also because frontal cortex is more relevant to ASD. 14
260 BA10 (anterior prefrontal cortex) and 28 BA44 (a part of the frontal cortex) samples are remained,
261 which resulted in a total of 17 control and 10 autism samples. For downstream analysis, the read
262 count table was firstly transformed in to FPKM (fragments per kilobase of exon model per million
263 reads mapped) table by customized R script.

264 GSE28475 dataset:

265 Postmortem frozen and formalin fixed brain tissue from autistic and control individuals were pre-
266 pared by standard RNA extraction protocol, and the expression profiles of each samples were
267 measured by Illumina HumanRef-8 v3.0 expression beadchip. Only frontal cortex samples (N=25)
268 of the micro-array expression data (N=143) used in this study, which resulted in a total of 17 con-
269 trol and 8 autism samples. The data was downloaded from Gene Expression Omnibus (GEO) under
270 accession number GSE28475. Expression table were log2 transformed and normalized with limma
271 (*Ritchie et al., 2015b*) package in R.

272 GSE28521 dataset:

273 Total RNA was extracted from approximately 100mg of postmortem brain tissue representing
274 frontal cortex, temporal cortex and the cerebellum, from autistic and control individuals. The data
275 was also downloaded from GEO data under accession number GSE28521. The expression profiles
276 of each samples were quantified by Illumina HumanRef-8 v3.0 expression beadchip, and were nor-
277 malized by a same pipeline as GSE28475 dataset. Only frontal cortex samples ($N = 32$) of the
278 micro-array expression data ($N = 79$) used in this study, which resulted in a total of 16 control and
279 16 autism samples.

280 Pairwise similarity comparison.

281 For each dataset, the expression profiles of every two samples were extracted, and similarity be-
282 tween them are calculated by Pearson' R correction. The distance between two samples were
283 measured correlation distance, and the dendrogram were generated by hierarchical clustering.
284 The comparision plots were rendered by ComplexHeatmap package.

285 Transcriptome variability.

286 The expression table of each dataset was split into autism subset and control subset respectively.
287 For each pair, the coefficient of variations (CV) were calculated both for each gene and for each
288 sample. CV was defined as the standard deviation of the expression level divided by its average.
289 The significance of difference between autism and control subset was verified by Student's t-test.

290 Sample clustering.

291 Expression profiles were in Gupta's dataset were clustered by t-SNE (t-distributed stochastic neigh-
292 bor embedding) strategy. For simplicity, the diverse profile can be divided into two main categories.
293 The samples were labeled by two unsupervised methods without the input of clinical information.

294 k-means clustering and hierarchical clustering method showed consistent results. The analysis
295 were achieved by Rtsne package and some customized scripts.

296 **Differential expression genes (DEGs) analysis.**

297 13 samples in cluster 1 and 14 samples in cluster 2 were included in this analysis. Gene-level dif-
298 ferential expression was analyzed using limma package. In brief, a linear model was fit for each
299 gene given the expression table of Gupta's dataset, least squares method was chosen in the fitting
300 process. Then the fitted model was re-orientates with a experimental design matrix, and the co-
301 efficients were re-calculated in terms of the contrasts. Empirical Bayes moderation strategy were
302 used to calibrate the t-statistics, F-statistic, and the odds ratio of differential expression genes. For
303 RNA-sequencing data, genes with an absolute fold change (FC) greater 2 and a p-value less than
304 0.05 were selected for the downstream analysis.

305 **Functional enrichment.**

306 DEGs were annotated by pre-defined terminologies such as Gene ontology (GO) and KEGG path-
307 way, and over-representation analysis (ORA) were performed by clusterProfiler package.

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