



Meta-analysis of differentially expressed genes in autism based on gene expression data

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ABSTRACT. The purpose of this study was to identify differentially expressed (DE) genes and biological processes associated with changes in gene expression in autism. We performed a meta-analysis using new publicly available Gene Expression Omnibus (GEO) datasets of autism. We performed Gene Ontology (GO) enrichment analyses and pathway analysis using the Kyoto Encyclopedia of Genes and Genomes (KEGG). Ten GEO datasets, including 364 cases and 248 controls, were available for the meta-analysis. We identified 3105 genes that were consistently DE in autism (1425 upregulated and 1680 downregulated genes). We also found that 7 genes were associated with phospholipase A2 (PLA2), including *LYPLA2P1*, *PLA2G4D*, *PNPLA2*, *LYPLA2*, *PLA2G6*, *PLA2G7*, and *PLA2G5*. We found GO terms for molecular functions significantly enriched in structural constituent of ribosome (GO: 0003735, P = 1.87E-06) and transcription regulator activity (GO: 0030528, P = 8.86E-04), while for biological processes, the enriched GO terms were involved in translational elongation (GO: 0006414, P = 1.74E-12) and the response to cytokine stimuli (GO: 0034097, P = 2.76E-05). The most significant pathway in our KEGG analysis was the ribosome pathway (P = 7.90E-

12). Our meta-analysis identified genes that were consistently DE and biological pathways associated with gene expression changes in autism.

Key words: Autism; Differentially expressed genes; Expression data; Meta-analysis; Microarray

INTRODUCTION

Autism is a common, highly heritable neuro-developmental condition characterized by marked genetic heterogeneity (Durand et al., 2007). Various etiologies have been suggested for this complex syndrome. Though it is associated with a high degree of heritability, the specific genes responsible for autism remain unknown. Various other factors have been implicated, including immunological (Ashwood et al., 2006), neurological (Hashimoto et al., 1993), and environmental (London, 2000) factors. Thus, a fundamental question is whether autism represents an etiologically heterogeneous disorder in which a myriad genetic or environmental risk factors perturb common underlying molecular pathways in the brain (Geschwind, 2008). However, in contrast with many other brain disorders, including neurodegenerative diseases such as Parkinson's or Alzheimer's diseases, autism lacks a clear unifying pathology at the molecular, cellular, and systems levels.

Emerging evidence implies that abnormal fatty acid metabolism plays a contributing role in autism pathology. Recent literature suggests that fatty acid homeostasis may be altered in autism as a result of insufficient dietary supplementation, genetic defects, function of enzymes involved in their metabolism, or influence of various environmental agents such as infections, inflammation, or drugs. Phospholipase A2 (PLA2) is an enzyme involved in maintaining membrane phospholipids. There are 3 major types of PLA2 enzymes: the calcium-dependent group IV cytosolic PLA2, the group II secretory PLA2, and the group VI calcium-independent PLA2 (Sun et al., 2004). Elevated levels of PLA2 in red blood cells have been associated with neuropsychiatric disorders such as schizophrenia, depression, bipolar disorder, dyslexia, and autism (Horrobin and Bennett, 1999; Bell et al., 2004).

Determining global levels of gene expression regulation may be particularly important for understanding the pathological basis of diseases such as autism, in which multiple systems are affected. Alterations at the global level of gene expression regulation may be shared across systems, even when the tissue-specific genes affected by these global changes differ. High-throughput genomics technologies have improved our understanding of the complex interactions and networks involved in disease development. Microarrays measure the expression of thousands of genes simultaneously on a genome-wide scale (Golub et al., 1999). Alterations in gene profiles can be correlated to altered gene functions and biochemical activities. Microarray is a powerful tool that has rapidly increased as an investigational method in medical research.

Identification of gene expression signatures that differentiate the disease state from healthy controls is dependent on samples, sample size, heterogeneous data sets, and reproducibility (Ramasamy et al., 2008). Although many microarray studies have provided lists of differentially expressed (DE) genes, there are inconsistencies among studies resulting from limitations such as small sample sizes (Siddiqui et al., 2006). Data integration techniques, such as meta-analyses, combine available data and integrate information from multiple independent but related microarray studies to identify significant genes (Feichtinger et al., 2012). Combining data from various studies can enhance the reliability and generalizability of the results (Ramasamy et al., 2008) and can be used to more precisely estimate gene expression. In

particular, the benefit of increased statistical power can help to overcome the limitation of microarray studies. In this study, we used a new method to perform a meta-analysis of expression data of multiple gene expression data sets. To overcome the limitations of individual studies, resolve inconsistencies, and reduce the likelihood of random errors revealing false-positive or false-negative associations, we performed a microarray meta-analysis to identify DE genes and biological processes associated with gene expression changes in autism.

MATERIAL AND METHODS

Identification of eligible autism

ASD gene expression datasets

We first queried PubMed and related databases for expression profiling studies comparing autism and normal control tissues (NT). The following key words and their combinations were used: “autism, gene expression, microarray, genetics”. In addition, the Gene Expression Omnibus database (GEO, <http://www.ncbi.nlm.nih.gov/geo>) was also searched to identify any other relevant studies. The search results were limited to those published between 2000 and March 2013. We only retained the original experimental articles that analyzed gene expression profiling of autism and NT. Non-human studies, review articles, and integrated analysis of expression profiles were excluded. We conducted this meta-analysis in accordance with the guidelines provided in the PRISMA statement (The PRISMA Checklist S1). Data were extracted from the original studies by 2 independent reviewers. Any discrepancies between reviewers were resolved by consensus or consultation with a third reviewer. The following information was extracted from each identified study: GEO accession number, sample type, platform, number of cases and controls, references, and gene expression data.

Data preprocessing

Normalization is important for comparing microarray data sets. The heterogeneity of different datasets caused by using different platforms, different gene nomenclature, and different control tissues may make it difficult to directly compare studies. Thus, a global normalization method for minimizing inconsistency should be used. For this purpose, we used the Z-score transformation approach to calculate the expression intensities for each probe of the gene expression profiles. Z-scores were calculated according to the formula:

$$\text{Z score} = \frac{x_i - \bar{x}}{\delta}$$

where x_i represents raw intensity data for each gene; \bar{x} represents average gene intensity within a single experiment, and δ represents standard deviation (SD) of all measured intensities.

Statistical analysis

The significance analysis of the microarray software was then used to identify the DE genes between disease and control samples. This procedure combines the calculation of a Student *t*-test statistic value for each gene with subsequent permutation analysis and false

discovery rate (FDR) calculation. To obtain the best balance between the number of significant calls and the lowest FDR for the dataset tested, we selected genes showing at least 2-fold changes and an FDR less than 0.05 as significantly DE.

Functional classification of DE genes

To examine the biological significance of DE genes, we performed Gene Ontology (GO) enrichment analysis to investigate their functional distribution. The online-based software GeneCoDis3 (<http://genecodis.cnb.csic.es>) was used for this analysis. Fisher's exact test was used at P value < 0.1 and significance level was adjusted by a correction for FDR. In addition, we also performed pathway enrichment analysis based on the Kyoto Encyclopedia of Genes and Genomes (KEGG) database.

RESULTS

Overview of the studies included

In this study, we identified a total of 10 expression-profiling studies based on our inclusion criteria, which included 612 samples of 364 cases and 248 controls. The characteristics of studies included in this analysis are listed in Table 1 (Nishimura et al., 2007; Gregg et al., 2008; Hu et al., 2009a,b; Alter et al., 2011; Voineagu et al., 2011; Kuwano et al., 2011; Ginsberg et al., 2012). The data sets for GSE30573 and GSE28521 were examined in the same study, but GSE30573 was RNA - seqdata set, and the data sets we applied were almost microarray data sets except for GSE30573.

Table 1. Characteristics of individual studies included in the meta-analysis.

GEO ID	Sample source	Numbers (AU:NT)	Platform
GSE7329	Blood	15:15	GPL1708 Agilent-012391 G4112A
GSE6575	Blood	49:12	GPL570 AffymetrixU133 plus 2.0
GSE15451	Blood	21:17	GPL3427 TIGR 40K
GSE15402	Blood	87:29	GPL3427 TIGR 40K
GSE26415	Blood	42:42	GPL6480 Agilent-014850 4x44K G4112F
GSE28521	Brain	40:39	GPL6883 Illumina HumanRef-8 v3.0 expression beadchip
GSE30573	Brain	3:3	GPL9115 Illumina Genome Analyzer II
GSE25507	Blood	82:64	GPL570 AffymetrixU133 plus 2.0
GSE38609	Brain	9:9	GPL10558 Illumina HumanHT-12 V4.0 expression beadchip
GSE43076	Blood	16:18	GPL6480 Agilent-014850 4x44K G4112F

AU = Autism; NT = normal tissue.

Global changes in gene expression

To identify genetic markers involved in the development and progression of child autism, we determined the probe ID, for a microarray platform that represent a named gene, and the HUGO symbol of that gene, for each data set to the National Center for Biotechnology Information (NCBI) gene ID. The expression value was logarithmically transformed (base 2) and then transformed to a Z-score for global normalization. After filtering the normalized data, 33,502 genes were detected in more than 60% of the samples.

Using the assembled expression compendium, we investigated global shifts in gene expression between child autism and corresponding NTs, respectively. The significance analysis of the microarray method was used to identify DE genes between pathological and control samples. With the threshold of $FDR < 0.05$ and minimal 2-fold changes, a total of 3105 genes were found to be DE between child autism and NT. Among the 3105 DE genes, 1425 genes were upregulated and 1680 genes were downregulated. Lists of the top 20 most significantly up- or downregulated genes are provided in Tables 2 and 3, respectively. We also identified 7 genes associated with PLA2, including *LYPLA2P1*, *PLA2G4D*, *PNPLA2*, *LYPLA2*, *PLA2G6*, *PLA2G7*, and *PLA2G5* (Table 4).

Table 2. Top 20 upregulated differentially expressed genes.

Gene ID	Gene symbol	Combined ES	P value	Gene name
124975	GGT6	1.06E-02	2.60E-09	Gamma-glutamyltransferase 6
7475	WNT6	1.35E-02	2.62E-09	Wingless-type MMTV integration site family, member 6
84214	DKFZP434F142	1.70E+01	2.92E-09	Uncharacterized DKFZp434F142
283651	HMG2P46	3.69E-02	3.01E-09	High mobility group nucleosomal binding domain 2 pseudogene 46
678	ZFP36L2	1.91E-02	4.95E-09	ZFP36 ring finger protein-like 2
8352	HIST1H3C	2.10E+01	5.97E-09	Histone cluster 1, H3c
3126	HLA-DRB4	1.45E+01	7.01E-09	Major histocompatibility complex, class II, DR beta 4
8350	HIST1H3A	1.78E+00	1.22E-08	Histone cluster 1, H3a
129880	BBS5	9.34E+00	1.38E-08	Bardet-Biedl syndrome 5
2837	UTS2R	2.03E-02	1.59E-08	Urotensin 2 receptor
3045	HBD	9.67E-02	1.63E-08	Hemoglobin, delta
963	CD53	2.00E+01	1.65E-08	CD53 molecule
8290	HIST3H3	4.19E-03	1.67E-08	Histone cluster 3, H3
339665	SLC35E4	2.83E-02	1.78E-08	Solute carrier family 35, member E4
84757	MGC10814	6.11E-02	1.88E-08	Uncharacterized protein MGC10814
6181	RPLP2	2.06E-01	1.97E-08	Ribosomal protein, large, P2
79955	PDZD7	1.95E-02	2.03E-08	PDZ domain containing 7
147700	KLC3	3.49E-02	2.05E-08	Kinesin light chain 3
8717	TRADD	5.57E+04	2.14E-08	TNFRSF1A-associated via death domain
613126	LOC613126	7.33E-02	2.19E-08	Uncharacterized LOC613126

ES = effect size.

Table 3. Top 20 downregulated differentially expressed genes.

Gene ID	Gene symbol	Combined ES	P value	Gene name
283849	EXOC3L1	0.839180474	0.0088416	Exocyst complex component 3-like 1
677821	SNORA39	0.576012831	0.0041636	Small nucleolar RNA, H/ACA box 39
55716	LMBR1L	0.81735657	0.0079	Limb development membrane protein 1-like
693187	MIR602	0.825906322	0.001643	MicroRNA 602
90525	SHF	0.562686734	0.0092982	Src homology 2 domain containing F
339122	RAB43	0.82111752	0.0083847	RAB43, member RAS oncogene family
10984	KCNQ1OT1	0.790779915	0.00171585	KCNQ1 opposite strand/antisense transcript 1 (non-protein coding)
390260	OR6X1	0.851178751	0.0064821	Olfactory receptor, family 6, subfamily X, member 1
650683	LOC650683	0.740192555	0.0067242	Hypothetical protein LOC650683
386676	KRTAP10-9	0.809996476	0.0079572	Keratin associated protein 10-9
641804	LOC641804	0.78233216	0.0041796	Similar to GTF2I repeat domain containing 1 isoform 2
256892	OR51F1	0.737303349	0.006725	Olfactory receptor, family 51, subfamily F, member 1
344657	LRR1Q4	0.845407404	0.0093379	Leucine-rich repeats and IQ motif containing 4
3737	KCNA2	0.650380382	0.0097038	Potassium voltage-gated channel, shaker-related subfamily, member 2
284613	CYB561D1	0.795587453	0.0071833	Cytochrome b561 family, member D1
9820	CUL7	0.768716592	0.0063811	Cullin 7
8659	ALDH4A1	0.801344254	0.0027847	Aldehyde dehydrogenase 4 family, member A1
79228	THOC6	0.373313212	0.0081636	THO complex 6 homolog (Drosophila)
64946	CENPH	0.804828762	0.0079593	Centromere protein H
5877	RABIF	0.793222926	0.0056414	RAB interacting factor

Table 4. PLA2-associated differentially expressed genes.

Gene ID	Gene symbol	P value	Gene name
285840	<i>LYPLA2P1</i>	8.24E-03	Lysophospholipase II pseudogene 1
283748	<i>PLA2G4D</i>	1.36E-03	Phospholipase A2, group IVD (cytosolic)
57104	<i>PNPLA2</i>	5.58E-03	Patatin-like phospholipase domain containing 2
11313	<i>LYPLA2</i>	1.02E-03	Lysophospholipase II
8398	<i>PLA2G6</i>	8.52E-03	Phospholipase A2, group VI (cytosolic, calcium-independent)
7941	<i>PLA2G7</i>	3.62E-03	Phospholipase A2, group VII (platelet-activating factor acetylhydrolase, plasma)
5322	<i>PLA2G5</i>	8.95E-04	Phospholipase A2, group V

Functional annotation of DE genes

To gain insight into the biological roles of these DE genes, we performed GO categories enrichment analysis. GO provides a common descriptive framework and functional annotation and classification for gene sets analysis. GO categories are organized into 3 groups: biological process, molecular function, and cellular component. In our study, only the biological process and molecular function categories were considered. Using an FDR < 0.01 threshold, we identified 146 significant enrichments for DE genes. We identified GO terms for molecular functions significantly enriched in structural constituent of ribosome (GO: 0003735, P = 1.87E-06) and transcription regulator activity (GO: 0030528, P = 8.86E-04) (Table 5), while for biological processes, the enriched GO terms were translational elongation (GO: 0006414, P = 1.74E-12) and response to cytokine stimulus (GO: 0034097, P = 2.76E-05).

Table 5. GO enrichment of differentially expressed genes (top 15).

GO ID	Term	P value
Molecular functions		
GO: 0003735	Structural constituent of ribosome	1.87E-06
GO: 0030528	Transcription regulator activity	8.86E-04
GO: 0008134	Transcription factor binding	9.53E-04
GO: 0032393	MHC class I receptor activity	3.33E-03
GO: 0003723	RNA binding	4.01E-03
GO: 0043565	Sequence-specific DNA binding	4.03E-03
GO: 0016563	Transcription activator activity	4.31E-03
GO: 0003700	Transcription factor activity	4.39E-03
GO: 0030274	LIM domain binding	6.76E-03
GO: 0003950	NAD ⁺ ADP-ribosyltransferase activity	1.02E-02
GO: 0003677	DNA binding	1.21E-02
GO: 0003712	Transcription cofactor activity	1.44E-02
GO: 0005254	Chloride channel activity	1.79E-02
GO: 0005344	Oxygen transporter activity	1.80E-02
GO: 0016776	Phosphotransferase activity, phosphate group as acceptor	1.96E-02
Biological processes		
GO: 0006414	Translational elongation	1.74E-12
GO: 0034097	Response to cytokine stimulus	2.76E-05
GO: 0006412	Translation	3.39E-05
GO: 0045058	T cell selection	2.36E-04
GO: 0015908	Fatty acid transport	3.65E-04
GO: 0006325	Chromatin organization	1.10E-03
GO: 0051276	Chromosome organization	1.73E-03
GO: 0045449	Regulation of transcription	1.82E-03
GO: 0046649	Lymphocyte activation	2.01E-03
GO: 0042110	T cell activation	2.02E-03
GO: 0006916	Anti-apoptosis	2.16E-03
GO: 0006333	Chromatin assembly or disassembly	2.28E-03
GO: 0043067	Regulation of programmed cell death	2.68E-03
GO: 0043069	Negative regulation of programmed cell death	2.93E-03
GO: 0015909	Long-chain fatty acid transport	2.94E-03

To further evaluate the biological significance of the DE genes, we also performed a KEGG pathway enrichment analysis (Table 6). The most significant pathway in our KEGG analysis was the ribosome pathway ($P = 7.90E-12$). Furthermore, graft-versus-host disease ($P = 9.67E-03$) and primary immunodeficiency pathways ($P = 3.32E-02$) were found to be highly enriched.

Table 6. KEGG pathway enrichment of differentially expressed genes.

KEGG pathway	P value	Genes
Ribosome	7.90E-12	<i>LOC729362, LOC441073, LOC728139, LOC644464, RPS11, LOC388339, RPL37A, LOC100129685, RPL38, LOC644934, RPL14, RPS4X, LOC647285, LOC728576, LOC645174, LOC646766, LOC646966, LOC389156, RPL27A, LOC643358, LOC100131205, LOC100129882, RPLP0P2, SNORA7B, RPS19, LOC387867, RPL12P6, RPS4X, LOC729402, RPS6, LOC400652, RPLP2, LOC100128060, RPL18, LOC648729, LOC100129902, LOC389141, LOC730029, LOC389342, LOC440575, LOC642892, RPS10P7, LOC100129424, LOC388556, LOC653156, RPL13, RPL10, LOC440737, RPL7A, LOC100128936, LOC728782, RPS27, LOC388474, LOC391833, RPL10L, RPS21, LOC653737, LOC441034</i>
Graft-versus-host disease	9.67E-03	<i>HLA-DRB4, KLRD1, KIR3DL1, CD28, KIR2DL2, KIR2DL3, PRF1, GZMB, HLA-B, IL1B, HLA-F, HLA-E, HLA-DRB1</i>
Primary immunodeficiency	3.32E-02	<i>CD40LG, CD4, CD40, CIITA, UNG, RFXAP, CD3D, CD3E, CD8B, CD79A</i>

DISCUSSION

Various genes are DE in individuals with autism, and identifying the most important genes and pathways associated with the disease is very important. We used a meta-analysis approach of DE genes from microarray datasets to identify genes that were consistently DE at a statistically significant level, and performed GO enrichment analysis and pathway analysis using KEGG.

We performed a meta-analysis using 10 publicly available GEO data sets to identify common biological mechanisms involved in the pathogenesis of autism. Nine of these GEO data sets were based on microarray data, while the GSE30573 dataset was from RNA sequencing determined in the same study as GSE28521. In 3 studies, postmortem brain tissue from individuals with autism was analyzed to show that the glutamate neurotransmitter system is altered in patients with autism, while other studies examined blood cells from autistic individuals. We identified genes that were consistently up- or downregulated, showed significant GO enrichment, and pathways associated with autism. A total of 3105 genes across the studies were consistently DE in autism (1425 upregulated and 1680 downregulated). Among these 3105 DE genes, 7 genes were associated with PLA2. To identify the biological processes associated with gene expression changes in autism, we performed GO analysis for the DE genes. The most significant enrichment among the list of molecular functions was the GO category of structural constituents of the ribosome ($P = 1.87E-06$). Other significant GO categories for biological processes included translational elongation ($P = 1.74E-12$) and the response to cytokine stimulus ($P = 2.76E-05$). The most significant pathway in our KEGG analysis was ribosome pathway ($P = 7.90E-12$). Furthermore, the graft-versus-host disease ($P = 9.67E-03$) and primary immunodeficiency pathways ($P = 3.32E-02$) were found to be highly enriched.

Using genome-wide differential display approaches, a number of recent studies have highlighted single-nucleotide polymorphisms, copy number variants, and epigenetic factors involved in the dysregulated expression of candidate genes related to autism occurrence (Bill and Geschwind, 2009). Putative and known candidates contributing to autism susceptibility are categorized based on the differentiation of neurons (e.g., *DISC1*, *MET*, *PTEN*, and *ITGB3*),

neuronal cell adhesion (e.g., *NRXN1*, *NLGN3*, and *NLGN4X*), transmission of nervous system (e.g., *OXTR*, *SLC6A4*, *GABRB3*, and *SHANK3*), and regulation of neuronal activity (e.g., *FMRI*, *MECP2*, and *UBE3A*) (Ingram et al., 2000; Martin et al., 2000; Wassink et al., 2001; Jaimain et al., 2002; Campbell et al., 2006; Hu et al., 2006; Talebizadeh et al., 2006; Durand et al., 2007). In this study we identified autism susceptibility genes such as *WNT2*, *EGR2*, *HOXA1*, and *SHAK3* among the 3105 differentially expressed genes. One of the underlying biological components of neuro-developmental disorders may involve dysregulation of phospholipid metabolism. Therefore, we also identified genes associated with PLA2, including *LYPLA2P1*, *PLA2G4D*, *PNPLA2*, *LYPLA2*, *PLA2G6*, *PLA2G7*, and *PLA2G5*, among these DE genes identified. Evidence has accumulated regarding elevated plasma levels of PLA2 in schizophrenia patients compared with healthy controls. Three single-nucleotide polymorphisms in the gene encoding for cytosolic PLA2 have been linked to schizophrenia and were found to play a role in the etiology of this disorder (Wei et al., 1998; Tao et al., 2005). Interestingly, the genes encoding human calcium-independent PLA2 and secretory PLA2 map to regions on chromosome 8q23-24 and 7q31, respectively (Meyer et al., 1996), which have been previously linked to autism (Chen et al., 2005; Combi et al., 2010). This suggests that the altered levels of arachidonic acid and docoheptaenoic acid in individuals with autism may be attributed to abnormalities in PLA2. Indeed, significantly increased activity of type IV PLA2 has been reported in the red blood cells of patients with autism and Asperger's syndrome compared to controls, strengthening the hypothesis that abnormal lipid metabolism occurs in autism (Bell et al., 2004, 2010). The increased PLA2 activity in individuals with autism may cause elevated breakdown of polyunsaturated fatty acids and their subsequent reduced incorporation into membrane phospholipids. Overall, the literature suggests a link between abnormalities in PLA2 enzymes and some psychiatric disorders, including autism spectrum disorders, which substantiates the importance of downstream lipid signaling molecules in proper nervous system functioning.

Interestingly, the most significant pathway in our KEGG analysis was the ribosome pathway. Ribosomal proteins play a crucial role in the regulation of protein synthesis. Therefore, their expression must be strictly controlled (Caldarola et al., 2009). This finding suggests a generalized and non-targeted process and may be a result of deregulation of other pathways. Several lines of evidence have identified a link between ribosome biogenesis and diseases such as cancer, anemia, and aging. A recent review also emphasized that protein synthesis is tightly linked to the regulation of neurological processes and cell growth (Twiss and Fainzilber, 2009). Deregulation of genes encoding ribosomal proteins may indirectly reflect an atypical process of neurological development in subjects with autism.

There were some limitations to our study. First, heterogeneity and confounding factors may have distorted our analysis. Clinical samples may be heterogeneous with respect to clinical activity, severity, or gender. Second, there were differences in gene expression between tissues such as the blood and brain that were not taken into account. However, our meta-analysis integrated data from different studies, enabling us to detect genes that would otherwise not have been identified. Despite these limitations, our findings have important implications for the pathophysiology of autism.

REFERENCES

- Alter MD, Kharkar R, Ramsey KE, Craig DW, et al. (2011). Autism and increased paternal age related changes in global levels of gene expression regulation. *PLoS One* 6: e16715.

- Ashwood P, Wills S and Van de Waer J (2006). The immune response in autism: a new frontier for autism research. *J. Leukoc. Biol.* 80: 1-15.
- Bell JG, MacKinlay EE, Dick JR, MacDonald DJ, et al. (2004). Essential fatty acids and phospholipase A2 in autistic spectrum disorders. *Prostaglandins Leukot. Essent. Fatty Acids* 71: 201-204.
- Bell JG, Miller D, MacDonald DJ, MacKinlay EE, et al. (2010). The fatty acid compositions of erythrocyte and plasma polar lipids in children with autism, developmental delay or typically developing controls and the effect of fish oil intake. *Br. J. Nutr.* 103: 1160-1167.
- Bill BR and Geschwind DH (2009). Genetic advances in autism: heterogeneity and convergence on shared pathways. *Curr. Opin. Genet. Dev.* 19: 271-278.
- Caldarola S, De Stefano MC, Amaldi F and Loreni F (2009). Synthesis and function of ribosomal proteins-fading models and new perspectives. *FEBS J.* 276: 3199-3210.
- Campbell DB, Sutcliffe JS, Ebert PJ, Militerni R, et al. (2006). A genetic variant that disrupts MET transcription is associated with autism. *Proc. Natl. Acad. Sci. U. S. A.* 103: 16834-16839.
- Chen GK, Kono N, Geschwind DH and Cantor RM (2005). Quantitative trait locus analysis of nonverbal communication in autism spectrum disorder. *Mol. Psychiatry* 11: 214-220.
- Combi R, Redaelli S, Beghi M, Clerici M, et al. (2010). Clinical and genetic evaluation of a family showing both autism and epilepsy. *Brain Res. Bull.* 82: 25-28.
- Durand CM, Betancur C, Boeckers TM, Bockman J, et al. (2007). Mutations in the gene encoding the synaptic scaffolding protein SHANK3 are associated with autism spectrum disorders. *Nat. Genet.* 39: 25-27.
- Feichtinger J, Thallinger GG, McFarlane RJ and Larcombe LD (2012). Microarray Meta-Analysis: From Data to Expression to Biological Relationships. In: Computational Medicine. Springer, New York, 59-77.
- Geschwind DH (2008). Autism: many genes, common pathways? *Cell* 135: 391-395.
- Ginsberg MR, Rubin RA, Falcone T, Ting AH, et al. (2012). Brain transcriptional and epigenetic associations with autism. *PLoS One* 7: e44736.
- Golub TR, Slonim DK, Tamayo P, Huard C, et al. (1999). Molecular classification of cancer: class discovery and class prediction by gene expression monitoring. *Science* 286: 531-537.
- Gregg JP, Lit L, Baron CA, Hertz-Picciotto I, et al. (2008). Gene expression changes in children with autism. *Genomics* 91: 22-29.
- Hashimoto T, Tayama M, Miyazaki M, Murakawa K, et al. (1993). Brainstem and cerebellar vermis involvement in autistic children. *J. Child. Neurol.* 8: 149-153.
- Horrobin DF and Bennett CN (1999). New gene targets related to schizophrenia and other psychiatric disorders: enzymes, binding proteins and transport proteins involved in phospholipid and fatty acid metabolism. *Prostaglandins Leukot. Essent. Fatty Acids* 60: 141-167.
- Hu VW, Frank BC, Heine S, Lee NH, et al. (2006). Gene expression profiling of lymphoblastoid cell lines from monozygotic twins discordant in severity of autism reveals differential regulation of neurologically relevant genes. *BMC Genomics* 7: 118.
- Hu VW, Nguyen A, Kim KS, Steinberg ME, et al. (2009a). Gene expression profiling of lymphoblasts from autistic and nonaffected sib pairs: altered pathways in neuronal development and steroid biosynthesis. *PLoS One* 4: e5775.
- Hu VW, Sarchana T, Kim KS, Nguyen A, et al. (2009b). Gene expression profiling differentiates autism case-controls and phenotypic variants of autism spectrum disorders: evidence for circadian rhythm dysfunction in severe autism. *Autism Res.* 2: 78-97.
- Ingram JL, Stodgell CJ, Hyman SL, Figlewicz DA, et al. (2000). Discovery of allelic variants of HOXA1 and HOXB1: genetic susceptibility to autism spectrum disorders. *Teratology* 62: 393-405.
- Jamain S, Betancur C, Quach H, Philippe A, et al. (2002). Linkage and association of the glutamate receptor 6 gene with autism. *Mol. Psychiatry* 7: 302-310.
- Kuwano Y, Kamio Y, Kawai T, Katsuura S, et al. (2011). Autism-associated gene expression in peripheral leucocytes commonly observed between subjects with autism and healthy women having autistic children. *PLoS One* 6: e24723.
- London EA (2000). The environment as an etiologic factor in autism: a new direction for research. *Environ. Health Perspect.* 108: 401-404.
- Martin ER, Menold MM, Wolpert CM, Bass MP, et al. (2000). Analysis of linkage disequilibrium in gamma-aminobutyric acid receptor subunit genes in autistic disorder. *Am. J. Med. Genet.* 96: 43-48.
- Meyer AH, Schmuck K, Morel C, Wishart W, et al. (1996). Localization of a gene coding for the phospholipase A2-L subtype (PLA2L) to human chromosome 8q24-qter. *Genomics* 38: 435-437.
- Nishimura Y, Martin CL, Vazquez-Lopez A, Spence SJ, et al. (2007). Genome-wide expression profiling of lymphoblastoid cell lines distinguishes different forms of autism and reveals shared pathways. *Hum. Mol. Genet.* 16: 1682-1698.
- Ramasamy A, Mondry A, Holmes CC and Altman DG (2008). Key issues in conducting a meta-analysis of gene expression

- microarray datasets. *PLoS Med.* 5: e184.
- Siddiqui AS, Delaney AD, Schnerch A, Griffith OL, et al. (2006). Sequence biases in large scale gene expression profiling data. *Nucleic Acids Res.* 34: e83-e83.
- Sun GY, Xu J, Jensen MD and Simonyi A (2004). Phospholipase A2 in the central nervous system: implications for neurodegenerative diseases. *J. Lipid Res.* 45: 205-213.
- Talebizadeh Z, Lam DY, Theodoro MF, Bittel DC, et al. (2006). Novel splice isoforms for NLGN3 and NLGN4 with possible implications in autism. *J. Med. Genet.* 43: e21.
- Tao R, Yu Y, Zhang X, Guo Y, et al. (2005). Cytosolic PLA2 genes possibly contribute to the etiology of schizophrenia. *Am. J. Med. Genet. B Neuropsychiatr. Genet.* 137: 56-58.
- Twiss JL and Fainzilber M (2009). Ribosomes in axons - scrounging from the neighbors? *Trends Cell Biol.* 19: 236-243.
- Voineagu I, Wang X, Johnston P, Lowe JK, et al. (2011). Transcriptomic analysis of autistic brain reveals convergent molecular pathology. *Nature* 474: 380-384.
- Wassink TH, Piven J, Vieland VJ, Huang J, et al. (2001). Evidence supporting WNT2 as an autism susceptibility gene. *Am. J. Med. Genet.* 105: 406-413.
- Wei J, Lee KH and Hemmings GP (1998). Is the cPLA2 gene associated with schizophrenia? *Mol. Psychiatry* 3: 480-481.