Research Article

LCK as a Potential Therapeutic Target for Acute Rejection after Kidney Transplantation: A Bioinformatics Clue

Linpei Jia, Rufu Jia, Yinping Li, Xiaoxia Li, Qiang Jia, and Hongliang Zhang

1Department of Nephrology, Xuanwu Hospital of Capital Medical University, Changchun Street 45#, Beijing 100053, China
2Central Hospital of Cangzhou, Xinhua Middle Street 201#, Cangzhou, Hebei Province 061001, China
3Department of Life Sciences, The National Natural Science Foundation of China, Shuangqiu Road 83#, Beijing 100085, China

Correspondence should be addressed to Linpei Jia; anny_069@163.com, Rufu Jia; zxyy5688@126.com, and Hongliang Zhang; drzhl@hotmail.com

Received 22 November 2017; Revised 12 March 2018; Accepted 10 April 2018; Published 7 June 2018

Academic Editor: Nejat K. Egilmez

Copyright © 2018 Linpei Jia et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Objectives. We aim to identify the key biomarker of acute rejection (AR) after kidney transplantation via bioinformatics methods.

Methods. The gene expression data GSE75693 of 30 samples with stable kidney transplantation recipients and 15 AR samples were downloaded and analyzed by the limma package to identify differentially expressed genes (DEGs). Then, Gene Ontology (GO) functional enrichment analysis and Kyoto Encyclopedia of Genes and Genomes (KEGG) pathway analysis were done to explore the biological functions and potential important pathways of DEGs. Finally, protein-protein interactions (PPIs) and literature mining were applied to construct the cocitation network and to select the hub protein.

Results. A total of 437 upregulated genes and 353 downregulated genes were selected according to $P < 0.01$ and $\log_2$ (fold change) $> 1.0$. DEGs of AR are mainly located on membranes and impact the activation of receptors in immune responses. In the PPI network, Src kinase, lymphocyte kinase (LCK), CD3G, B2M, interferon-γ, CD3D, tumor necrosis factor, VAV1, and CD3E in the T cell receptor signaling pathway were selected as important factors, and LCK was identified as the hub protein.

Conclusion. LCK, via acting on T-cell receptor, might be a potential therapeutic target for AR after kidney transplantation.

1. Introduction

Kidney transplantation is widely accepted as a standard life-saving therapy for end-stage chronic kidney disease [1]. Frequently as the last resort, kidney transplantation may prolong patients’ survival and improve their life quality [2]. Immunosuppressants are routinely prescribed to recipients to promote graft survival after transplantation [3]. Despite the standard use of immunosuppressants, however, acute rejection (AR) is sometimes inevitable, which usually occurs days to months after transplantation [4]. The short- and long-term impacts of AR on graft loss and even morbidity have been extensively studied [5].

According to the distinct key players in the pathogenesis, AR is classified into two types, i.e., acute T cell-mediated rejection (TCMR) and acute antibody-mediated rejection (AMR). Although the precise mechanism of TCMR is still unclear, cell-mediated cytotoxicity of parenchymal cells and local cytokine release are two possible causes [6]. By contrast, AMR is caused by circulating antibodies of recipients, which are mainly antibodies against donor human leukocyte antigen (HLA). Then T helper (Th) cell and macrophages participate in the immune response to clear allogenic cells and to assist differentiation of B cells [7]. Thus, T cells play important roles in both TCMR and AMR.

Once AR occurs, a short course of intensive immunomodulation is needed. Pulse steroid therapy, alteration of immunosuppressants, monoclonal antibodies and combinations thereof are common therapies for AR [8]. Among others, a high dose of steroids and immunosuppressants might lead to a high risk of infection and other side effects [9]. In recent decades, monoclonal antibodies, such as antilymphocyte globulin, antithymocyte globulin, and T10B9, an monoclonal antibody against the T cell receptor (TCR) [10], have been applied to deal with AR [9]. However, side effects such as infection and tumorigenesis may still occur occasionally.
Webster et al. compared the efficacy between monoclonal antibodies and steroids; they found that monoclonal antibodies appeared better than steroids for reversing first acute cellular rejection and preventing graft loss, but there was little or no difference in subsequent rejection and the survival rate [9]. Thus, further insight into the mechanism of AR and identification of the key step in the pathogenesis may shed light on the discovery of therapeutic targets for AR [12].

Gene expression analysis by bioinformatics methods has been widely used in genomics and biomedical studies, which helps clarify the molecular events underlying human biology and diseases [13]. Data mining of the available microarray data could help narrow down the study scope so as to find research gaps [14]. In this study, we analyzed the public microarray data by using bioinformatics methods, including differentially expressed genes (DEGs) analysis, gene enrichment methods, protein-protein interaction (PPI) analysis, and literature mining, in order to identify the key factors of AR in kidney transplantation recipients and to provide new insights into the treatment of AR.

2. Materials and Methods

2.1. Affymetrix Microarray Data and Sample Selection. First, we downloaded the microarray dataset GSE75693 from the public Gene Expression Omnibus (GEO) database (http://www.ncbi.nlm.nih.gov/geo/). The dataset GSE75693 consists of the gene expression information of kidney biopsies from 30 stable renal allograft recipients, 15 patients with AR, 15 with BK virus nephropathy, and 12 with chronic allograft nephropathy. All subjects were pediatric and young adult recipients who received transplantation between 2000 and 2011 at the Lucile Packard Children’s Hospital of Stanford University [15]. AR was defined at minimum, as per Banff schema, a tubulitis score ≥1 accompanied with an interstitial inflammation score ≥1. Normal allografts were considered as an absence of significant injury pathology of Banff schema [15]. Data of the 30 stable renal allograft recipients and the 15 patients with AR were used to investigate the potential mechanism of AR. In the original study, AR patients were diagnosed by professional pathologists and scored by the Banff immunohistochemical and by Cytoscape (http://www.cytoscape.org/). The proteins with higher degrees of interaction were considered as hub proteins [19].

The array data were based on the platform of GPL570 Affymetrix Human Gene U133 Plus 2.0 Array (Affymetrix Inc., Santa Clara, CA, USA). The raw data were preprocessed by Robust Multiarray Average [16] algorithm in affy package of Bioconductor (http://www.bioconductor.org/), including background correction, normalization, and calculation of gene expressions.

2.2. DEG Analysis. We used the limma package of Bioconductor to analyze DEGs between BKVN and nonallograft injury patients in R project (Supplementary 1). Linear models were constructed for gene expression data of AR and stable renal allograft samples, respectively. The contrast model was used to compare gene expression differences between the two groups. P values were calculated by the Bayesian t-test and adjusted by false discovery rate. DEGs were selected based on the threshold P < 0.01 and \[\log_2 \text{(fold change)}\] > 1.0 [17]. The P value herein was used to test if the gene was differentially expressed between the AR and the stable groups with the [fold change] > 2.0.

2.3. Enrichment Analysis of DEGs. By Gene Ontology (GO) and the Kyoto Encyclopedia of Genes and Genomes (KEGG) in DEG enrichment analysis, we further investigated the potential mechanisms of AR. GO annotated genes by a defined, structured, and controlled vocabulary [18], including molecular function (MF), biological process (BP), and cellular components (CC), while KEGG assigns DEGs to specific pathways [19]. GO and KEGG can be performed in website of Database for Annotation, Visualization and Integrated Discovery (DAVID, http://david.abcc.ncifcrf.gov/). The potential GO annotation and pathways were selected based on P < 0.01 and count ≥ 5 [20].

2.4. PPI Network Construction. Connections and interaction networks of DEGs mean PPI. We uploaded the DEGs into the website of STRING (Search Tool for the Retrieval of Interacting Genes/Proteins, http://string-db.org/), which is the web source of biological database. According to the official explanation of STRING, the confidence score is the approximate probability that a predicted link exists between two proteins in the same metabolic map in the KEGG database (Getting Started in https://string-db.org/cgi/help.pl). Thus, PPIs of DEGs were selected with the threshold of score (high confidence) > 0.7 [20]. Then the analysis results were downloaded and modified by Cytoscape (http://www.cytoscape.org/). The proteins with higher degrees of interaction were considered as hub proteins [19].

2.5. Literature Mining. According to the analysis of STRING, hot proteins in the PPI were put into GenCLiP 2.0 (http://ci.smu.edu.cn/GenCLiP2.0/confm_keywords.php), which is an online tool for literature mining of gene functions. In the website, biological keywords of hot proteins in previous literature database were analyzed by Gene Cluster with the Literature Profiles module with the threshold of P ≤ 1 × 10^-6 and hits ≥ 6 [19]. And the Literature Mining Gene Networks module was used to show the cocitation network of hot proteins. After combining the results of literature mining and KEGG analysis, the primary pathways in AR were determined.

2.6. Hub Protein Selection by CytoNCA. In Cytoscape, the separated proteins from the network were removed. All nodes in PPIs were analyzed by CytoNCA. According to degree centrality, betweenness centrality, and subgraph centrality [16], the hub protein, which interacts most frequently with other proteins and works like a hub in the network, was selected. Finally, proteins associated with hub proteins at degree ≥ 20 were selected to construct the significant network about the mechanism of AR [21].
3. Results

3.1. Seven Hundred and Ninety DEGs Were Identified. Microarray data in the GSE75693 dataset were downloaded for further analysis. DEGs of AR were identified by the limma package following the process of linear model, contrast model, and DEGs selection. Compared with no-allograft injury patients, 790 genes are expressed differentially in AR patients based on the criteria of $P < 0.01$ and $|\log_2(\text{fold change})| > 1.0$, including 437 upregulated genes and 353 downregulated genes. The hierarchical cluster analysis was done to show the distribution of DEGs (Figure 1).

3.2. DEGs of AR Mainly Enriched in the Cell Receptor Functions. For further analyzing biological functions of DEGs, we uploaded DEGs in DAVID. GO and pathway terms were selected. In MF ontology, DEGs mainly enriched in 27 categories (Supplementary 2, Figure 2(a)) including the protein homodimerization activity (53 genes), receptor binding (26 genes), and receptor activity (26 genes). In BP
ontology, 94 terms were identified, and the majority of enriched categories are the immune response (83 genes), signal transduction (81 genes), and the inflammatory response (57 genes), which focused on the immune process (Supplementary 3, Figure 2(b)). Distribution of DEGs on cells was shown in CC ontology. Proteins of DEGs were mostly located on membranes of cell or organelles, including integral component of membranes (275 genes) and plasma membranes (263 genes) (Supplementary 4, Figure 2(c)). Other important CC categories are the extracellular exosome (182 genes), extracellular region (102 genes), and the extracellular space (83 genes). In KEGG analysis, 23 potential pathways in AR presented the greatest statistical significance. (b) Results of BP analysis. The immune response presented the least P value and the maximum of genes. (c) Results of CC analysis. Most of DEGs located on integral component of membranes, while the antigen binding has the greatest statistical significance. (d) Results of pathway analysis. Both the maximum of gene counts and lowest P value appeared in the category of cytokine-cytokine receptor interaction.

3.3. TCR Signaling Transduction Is the Main Pathway in the Pathogenesis of AR. At first, 790 DEGs were uploaded in STRING website. Then 254 genes with score > 0.7 (high confidence) were selected to construct the PPI network by Cytoscape (Figure 3). Top eight hot genes, including LCK, CD3G, B2M, IFNG, CD3D, TNF, VAV1, and CD3E, were put into GenCLiP 2.0 for analysis of Gene Cluster with Literature Profiles and Literature Mining Gene Networks. Results of gene clustering indicated that keywords of hot genes reported in literature were immune response, cell activation, cell differentiation, cell surface, T-cell activation, signal transduction, and plasma membrane (Figure 4(a)). Information of the cocitation network was shown in Figure 4(b) and Table 1. LCK and VAV1 work as links between CD3E and IFNG.
Combined with pathway analyses, 7 hot genes, except for B2M, participate in the TCR signaling pathway, and LCK, VAV1, IFNG, and TNF participate in the natural killer cell-mediated cytotoxicity pathway.

3.4. LCK Is the Key Factor in AR. Each DEG was evaluated according to degree centrality, betweenness centrality, and subgraph centrality, respectively, in CytoNCA (Table 2). LCK ranked top 5 in all centralities indicating the important role of LCK in the pathogenesis of AR. The other hub proteins are CD3G and IFNG. Hub nodes and proteins directly associated with hubs constructed an interaction network (Figure 5), including 27 upregulated and 1 downregulated proteins. EGF is the only downregulated protein in the final network.

4. Discussion

In the present study, we aimed at investigating potential therapeutic targets for AR after kidney transplantation. First,
437 upregulated genes and 353 downregulated genes were selected as DEGs of AR compared with nonrejection recipients. According to gene enrichment, DEGs of AR are mainly located on membranes and participate in the TCR signaling pathway. We identified LCK as the potential key factor in the pathogenesis of AR.

By GO annotation in DAVID, we further explored the biological functions of DEGs. The results of functional annotations helped us infer the possible effects of DEGs on how AR occurs. According to results of BP, CC, and MF ontologies, the majority of DEGs were enriched in functions of membrane receptors in the immune process. AR in kidney transplantation is generally considered as an alloimmune response process involving networks of interacting cells throughout the body [22]. Our BP analysis showed that the mechanism of AR was primarily focused on immune process, and this finding is consistent with previous studies [6, 23]. Then the CC ontology indicated that most of DEGs were membrane structures, such as proteins on integral component of membrane and plasma membrane. Based on previous studies, AR may be mediated by cellular and/or humoral mechanisms [7]. Approximately 90% of AR is TCMR, which involves CD4+ and CD8+ T cells by activating perforin/granzyme degranulation pathways [24]. Regardless of the recognition of antigens in TCMR and AMR or the release of accessory molecules, such as cytokines, signaling molecules, and adhesion molecules, receptors on membrane play important roles [25]. Meanwhile, we also found that a majority of DEGs were involved in protein homodimerization in MF ontology. This indicated that protein homodimerization activity is the main structure transformation and activation of receptors implicated in the antigen recognition and signaling transduction pathway in AR.

In the cocitation network, CD3D, CD3E, and CD3G, which are compositions of CD3 complex of TCR, interacted with each other to affect the assembly of TCR membrane complex and disturb T-cell responsiveness [27], especially CD3E [28]. After TCR engagement, the phosphorylation of CD3 immunoreceptor tyrosine-based activation motifs of CD3E in CD3 complex is combined with activated LCK, which is also called Src kinase lymphocyte kinase [29]. LCK is a member of protein tyrosine kinase involved in TCR signal transduction [30]. In TCR stimulation process, LCK can activate VAV GTPase to control the status of ezrin and...
moesin cytoskeletal protein phosphorylation, which regulates a series of protein translocation events [31, 32]. A previous study demonstrated that both AMR and TCMR manifested strong expressions of IFNG [33]. In AR, IFNG cooperated with TNF to increase antigen availability in rejection by enhancing HLA expression [34]. However, the relationship between VAV1 and IFNG has not been reported in the pathogenesis of AR, which could be further verified in animal and cellular experiments. Finally, via the PPI network analysis, we revealed that LCK in the TCR signaling pathway is the hub protein in the interaction network of DEGs, which underlies the notion that LCK might be a key link between antigen recognition and cytotoxicity.

The strength of our study is the combined use of several bioinformatics methods including DEG analysis, GO, KEGG, literature mining, STRING, and the PPI analysis. These data mining methods may corroborate each other and make the results reliable. However, our study has limitations. The sample size is relatively small. Different from conventional method, however, the limma method is proven effective in microarray analysis [35], even for a small sample size (2–5 cases) [36]. Nevertheless, the statistical power cannot be calculated in that the limma method comprises multistep data processing including both linear models and contrast models, as well as Bayesian analysis [37]. The data were downloaded from one dataset, and the sample size in GSE75693 was relatively small. The detailed demographic features of the cohort were unavailable in the published article. Due to the retrospective and bioinformatics nature of our study, further laboratory investigations on the cellular and animal levels are necessary to elucidate the pathogenesis of AR and to find potential therapeutic targets.

5. Conclusions

In summary, we revealed the potential important role of LCK in the pathogenesis of AR. LCK interacts with other 27 proteins and is actively involved in TCR pathway to activate the T cells in AR. LCK might be a potential therapeutic target for AR.
Conflicts of Interest
The authors state no conflict of interests.

Authors’ Contributions
Linpei Jia, Rufu Jia, and Hongliang Zhang contributed equally to the article as the correspondence authors.

Acknowledgments
The authors would like to thank Sidgel and his colleagues for uploading their dataset. The authors also thank Ms Wei Ren from the Chinese Academy of Sciences for the support of statistical analysis and R codes. The study was supported by grants from Wu Jieping Medical Foundation Clinical Research Funding (no. 320.6750.16050).

Supplementary Materials
Supplementary 1: R codes of differentially expressed genes. Supplementary 2: results of molecular function analysis. Twenty-seven terms were selected according to \( P < 0.01 \) and count \( \geq 5 \). Supplementary 3: results of biological process analysis. Ninety-four categories were selected according to \( P < 0.01 \) and count \( \geq 5 \). Supplementary 4: results of cellular component analysis. Twenty-one categories were selected according to \( P < 0.01 \) and count \( \geq 5 \). Supplementary 5: results of pathway analysis. Twenty-three pathways were selected according to \( P < 0.01 \) and count \( \geq 5 \). (Supplementary Materials)

References
[1] V. R. Mas, T. H. Le, and D. G. Maluf, “Epigenetics in kidney transplantation: current evidence, predictions, and future research directions,” *Transplantation*, vol. 100, no. 1, pp. 23–38, 2016.
[2] D. Zimmerman, A. A. House, S. J. Kim et al., “The risk of acute rejection following kidney transplant by 25-hydroxyvitamin D and 1,25-dihydroxyvitamin D status: a prospective cohort study,” *Canadian Journal of Kidney Health and Disease*, vol. 4, 2017.
[3] C. N. Crowson, R. D. Reed, B. A. Shelton, P. A. MacLennan, and J. E. Locke, “Lymphocyte-depleting induction therapy lowers the risk of acute rejection in African American pediatric kidney transplant recipients,” *Pediatric Transplantation*, vol. 21, no. 1, 2017.
[4] C. R. Dorf, W. S. Oetting, P. A. Jacobson, and A. K. Israni, “Genetics of acute rejection after kidney transplantation,” *Transplant International*, vol. 31, no. 3, pp. 263–277, 2018.
[5] M. Jalalzadeh, N. Mousavinasab, S. Peyrovi, and M. H. Ghadiani, “The impact of acute rejection in kidney transplantation on long-term allograft and patient outcome,” *Nephro-Urology Monthly*, vol. 7, no. 1, article e24439, 2015.
[6] K. L. Womer and B. Kaplan, “Recent developments in kidney transplantation—a critical assessment,” *American Journal of Transplantation*, vol. 9, no. 6, pp. 1265–1271, 2009.
[7] M. D. Parkes, P. F. Halloran, and L. G. Hidalgo, “Mechanistic sharing between NK cells in ABMR and effector T cells in TCMR,” *American Journal of Transplantation*, vol. 18, no. 1, pp. 63–73, 2018.
[8] M. D. Denton, C. C. Magee, and M. H. Sayegh, “Immunosuppressive strategies in transplantation,” *The Lancet*, vol. 353, no. 9158, pp. 1083–1091, 1999.
[9] A. C. Webster, S. Wu, K. Tallapragada, M. Y. Park, J. R. Chapman, and S. J. Carr, “Polyclonal and monoclonal antibodies for treating acute rejection episodes in kidney transplant recipients,” *Cochrane Database of Systematic Reviews*, no. 7, article CD004756, 2017.
[10] T. H. Waid, J. S. Thompson, M. Siemionow, and S. A. Brown, “T10B9 monoclonal antibody: a short-acting nonstimulating monoclonal antibody that spares y8 T-cells and treats and prevents cellular rejection,” *Drug Design, Development and Therapy*, vol. 3, pp. 205–212, 2009.
[11] G. Zaza, P. Tomei, S. Granata, L. Boschiero, and A. Lupo, “Monoclonal antibody therapy and renal transplantation: focus on adverse effects,” *Toxins*, vol. 6, no. 3, pp. 869–891, 2014.
[12] P. Erpicum, O. Hanssen, L. Weekers et al., “Non-invasive approaches in the diagnosis of acute rejection in kidney transplant recipients: Part II: omics analyses of urine and blood samples,” *Clinical Kidney Journal*, vol. 10, no. 1, pp. 106–115, 2017.
[13] A. B. Kimball, R. A. Grant, F. Wang, R. Osborne, and J. P. Tiesman, “Beyond the blot: cutting edge tools for genomics, proteomics and metabolomics analyses and previous successes,” *British Journal of Dermatology*, vol. 166, pp. 1–8, 2012.
[14] M. Mele, P. G. Ferreira, F. Reverter et al., “The human transcriptome across tissues and individuals,” *Science*, vol. 348, no. 6235, pp. 660–665, 2015.
[15] T. K. Sigdel, Y. Gao, J. He et al., “Mining the human urine proteome for monitoring renal transplant injury,” *Kidney International*, vol. 89, no. 6, pp. 1244–1252, 2016.
[16] Z. Lin and Y. Lin, “Identification of potential crucial genes associated with steroid-induced necrosis of femoral head based on gene expression profile,” *Gene*, vol. 627, pp. 322–326, 2017.
[17] A. Wang and G. Zhang, “Differential gene expression analysis in glioblastoma cells and normal human brain cells based on GEO database,” *Oncology Letters*, vol. 14, no. 5, pp. 6040–6044, 2017.
[18] M. Ashburner, C. A. Ball, J. A. Blake et al., “Gene ontology: tool for the unification of biology,” *Nature Genetics*, vol. 25, no. 1, pp. 25–29, 2000.
[19] L. Li, G. Wang, N. Li, H. Yu, J. Si, and J. Wang, “Identification of key genes and pathways associated with obesity in children,” *Experimental and Therapeutic Medicine*, vol. 14, no. 2, pp. 1065–1073, 2017.
[20] L. Zhang, Y. Huang, W. Zhuo, Y. Zhu, B. Zhu, and Z. Chen, “Identification and characterization of biomarkers and their functions for Lapatinib-resistant breast cancer,” *Medical Oncology*, vol. 34, no. 5, p. 89, 2017.
[21] G. Wang, L. Bi, G. Wang, F. Huang, M. Lu, and K. Zhu, “Microarray analysis to identify the similarities and differences of pathogenesis between aortic occlusive disease and abdominal aortic aneurysm,” *Vascular*, vol. 26, no. 3, pp. 301–314, 2017.
[22] R. Spreeuwo, S. Mitchell, and A. Hoffmann, “Training the 21st century immunologist,” *Trends in Immunology*, vol. 36, no. 5, pp. 283–285, 2015.
[23] O. Bestard and P. Cravedi, “Monitoring alloimmune response in kidney transplantation,” *Journal of Nephrology*, vol. 30, no. 2, pp. 187–200, 2017.
[24] J. L. Veale, L. W. Liang, Q. Zhang et al., “Noninvasive diagnosis of cellular and antibody-mediated rejection by perforin and granzyme B in renal allografts,” Human Immunology, vol. 67, no. 10, pp. 777–786, 2006.

[25] H. Sa, R. Leal, and M. S. Rosa, “Renal transplant immunology in the last 20 years: a revolution towards graft and patient survival improvement,” International Reviews of Immunology, vol. 36, no. 3, pp. 182–203, 2017.

[26] Y. Yoshioka, T. Suzuki, Y. Matsuo et al., “Protein lysine methyltransferase SMYD3 is involved in tumorigenesis through regulation of HER2 homodimerization,” Cancer Medicine, vol. 6, no. 7, pp. 1665–1672, 2017.

[27] M. Limbach, M. Saare, L. Tserel et al., “Epigenetic profiling in CD4+ and CD8+ T cells from Graves’ disease patients reveals changes in genes associated with T cell receptor signaling,” Journal of Autoimmunity, vol. 67, pp. 46–56, 2016.

[28] O. Ueda, N. A. Wada, Y. Kinoshita et al., “Entire CD3ε, δ, and γ humanized mouse to evaluate human CD3–mediated therapeutics,” Scientific Reports, vol. 7, article 45839, 2017.

[29] M. T. Pinto, T. M. Malta, E. S. Rodrigues et al., “T cell receptor signaling pathway is overexpressed in CD4(+) T cells from HAM/TSP individuals,” The Brazilian Journal of Infectious Diseases, vol. 19, no. 6, pp. 578–584, 2015.

[30] A. Fischer, C. Picard, K. Chemin, S. Dogniaux, F. le Deist, and C. Hivroz, “ZAP70: a master regulator of adaptive immunity,” Seminars in Immunopathology, vol. 32, no. 2, pp. 107–116, 2010.

[31] E. J. Allenspach, P. Cullinan, J. Tong et al., “ERM-dependent movement of CD43 defines a novel protein complex distal to the immunological synapse,” Immunity, vol. 15, no. 5, pp. 739–750, 2001.

[32] A. S. Shaw, “FERMing up the synapse,” Immunity, vol. 15, no. 5, pp. 683–686, 2001.

[33] P. F. Halloran, J. M. Venner, and K. S. Famulski, “Comprehensive analysis of transcript changes associated with allograft rejection: combining universal and selective features,” American Journal of Transplantation, vol. 17, no. 7, pp. 1754–1769, 2017.

[34] J. S. Pober, M. A. Gimbrone Jr., L. A. Lapierre et al., “Overlapping patterns of activation of human endothelial cells by interleukin 1, tumor necrosis factor, and immune interferon,” Journal of Immunology, vol. 137, no. 6, pp. 1893–1896, 1986.

[35] P. Baldi and A. D. Long, “A Bayesian framework for the analysis of microarray expression data: regularized t-test and statistical inferences of gene changes,” Bioinformatics, vol. 17, no. 6, pp. 509–519, 2001.

[36] C. Murie, O. Woody, A. Y. Lee, and R. Nadon, “Comparison of small n statistical tests of differential expression applied to microarrays,” BMC Bioinformatics, vol. 10, no. 1, p. 45, 2009.

[37] R. C. V. J. Gentleman, W. Huber, R. A. Irizarry, and S. Dudoit, Eds., “G.K. S. Limma: linear models for microarray data,” in Bioinformatics and Computational Biology Solutions Using R and Bioconductor. Statistics for Biology and Health, pp. 397–420, Springer, New York, NY, USA, 2005.