Using a Bayesian Hierarchical Model for Identifying Single Nucleotide Polymorphisms Associated with Childhood Acute Lymphoblastic Leukemia Risk in Case-Parent Triads

Ying Cao¹^o, Philip J. Lupo²^o, Michael D. Swartz¹, Darryl Nousome³, Michael E. Scheurer^{2*}

1 Division of Biostatistics, The University of Texas School of Public Health, Houston, Texas, United States of America, 2 Section of Hematology-Oncology, Department of Pediatrics, Baylor College of Medicine, Houston, Texas, United States of America, 3 Division of Epidemiology, Human Genetics and Environmental Sciences, The University of Texas School of Public Health, Houston, Texas, United States of America

Abstract

Childhood acute lymphoblastic leukemia (ALL) is a condition that arises from complex etiologies. The absence of consistent environmental risk factors and the presence of modest familial associations suggest ALL is a complex trait with an underlying genetic component. The identification of genetic factors associated with disease is complicated by complex genetic covariance structures and multiple testing issues. Both issues can be resolved with appropriate Bayesian variable selection methods. The present study was undertaken to extend our hierarchical Bayesian model for case-parent triads to incorporate single nucleotide polymorphisms (SNPs) and incorporate the biological grouping of SNPs within genes. Based on previous evidence that genetic variation in the folate metabolic pathway influences ALL risk, we evaluated 128 tagging SNPs in 16 folate metabolic genes among 118 ALL case-parent triads recruited from the Texas Children's Cancer Center (Houston, TX) between 2003 and 2010. We used stochastic search gene suggestion (SSGS) in hierarchical Bayesian models to evaluate the association between folate metabolic SNPs and ALL. Using Bayes factors among these variants in childhood ALL case-parent triads, two SNPs were identified with a Bayes factor greater than 1. There was evidence that the minor alleles of NOS3 rs3918186 (OR = 2.16; 95% CI: 1.51-3.15) and SLC19A1 rs1051266 (OR = 2.07; 95% CI: 1.25-3.46) were positively associated with childhood ALL. Our findings are suggestive of the role of inherited genetic variation in the folate metabolic pathway on childhood ALL risk, and they also suggest the utility of Bayesian variable selection methods in the context of case-parent triads for evaluating the role of SNPs on disease risk.

Citation: Cao Y, Lupo PJ, Swartz MD, Nousome D, Scheurer ME (2013) Using a Bayesian Hierarchical Model for Identifying Single Nucleotide Polymorphisms Associated with Childhood Acute Lymphoblastic Leukemia Risk in Case-Parent Triads. PLoS ONE 8(12): e84658. doi:10.1371/ journal.pone.0084658

Editor: Momiao Xiong, University of Texas School of Public Health, United States of America

Received June 5, 2013; Accepted November 18, 2013; Published December 19, 2013

Copyright: © 2013 Cao et al. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Funding: The genotyping for this work was supported by an Inter-Institutional Pilot Project (to M.E.S. and P.J.L.) from the Dan L. Duncan Cancer Center at Baylor College of Medicine, P30CA125123 (PI: Osborne). M.E.S. was also supported in part by an NCI Career Development Award, K07CA131505 and in part by Kurt Groten Family Research Scholars Award (P.J.L.). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing interests: The authors have declared that no competing interests exist.

* E-mail: scheurer@bcm.edu

• These authors contributed equally to this work.

Introduction

Childhood acute lymphoblastic leukemia (ALL) is considered to be a condition that arises from complex etiologies involving multiple factors. The absence of consistent environmental risk factors and the presence of modest familial associations suggest ALL is a complex trait with an underlying genetic component [1]. Although previous genome-wide association studies (GWAS) and candidate gene approaches have identified susceptibility loci contributing to the genetic basis of ALL, they only explain a small fraction of the heritability [1-5]. The identification of genetic factors associated with disease is complicated by complex genetic covariance structures and multiple testing issues. Both issues can be resolved with appropriate Bayesian variable selection methods.

Bayesian variable selection methods have demonstrated remarkable performance in a variety of settings, including those with weakly collinear covariates [6,7]. Additionally, stochastic search gene suggestion (SSGS) methods combine hierarchical Bayesian models with stochastic search variable selection technology to explore the posterior distribution on the model space to make inferences about the importance of genetic loci [6,8].

SSGS has many qualities that make it a strong candidate for the identification of loci involved in genetic susceptibility. Calibrated priors provide a strong balance of power and false discovery control [6,9,10]. The hierarchical nature of the priors for variable selection allows us to easily model the biological structure of single nucleotide polymorphisms (SNPs) grouped within genes. Also, many of the studies developing and stochastic search variable selection applying have performance demonstrated adequate when modeling correlated data, such as SNPs in linkage disequilibrium (LD) [6,11]. The hierarchical nature of the model provides a means to incorporate a priori known covariance structure into the model, which can improve variable selection among multiple predictors [7]. SSGS and other Bayesian variable selection methods model disease risk in a "holistic" manner, jointly considering all SNPs in question, while balancing power and false discovery control, which is important when evaluating high-dimensional data [6,9,10].

The present study was undertaken to extend our hierarchical Bayesian model for case-parent triads to incorporate single nucleotide polymorphisms (SNPs) and incorporate the biological grouping of SNPs within genes. This approach uses conditional logistic regression likelihood to model the probability of transmission to an affected child [6]. Additionally, the case-parent triad design provides an advantage to the traditional case-control design as it is immune to population stratification bias. This is because analyses are based on whether the inheritance of alleles by affected children deviates from Mendelian expectation rather than a comparison of genotypes between a case group and a control group [12,13]. As the folate metabolic pathway is suspected to play an important role in the development of childhood ALL due to its role in the synthesis, repair, and methylation of DNA [14], we selected 128 tagging SNPs in 16 folate metabolic genes (Table 1), which is an extension of our previous assessment of folate metabolic genes and childhood ALL [15].

Materials and Methods

Study Population

The study population included 118 ALL case-parent triads recruited from the Childhood Cancer Epidemiology and Prevention Center at Texas Children's Hospital (Houston, TX) between 2003 and 2010. Both males and females, and individuals of all racial/ethnic groups were eligible to participate. After written informed consent was obtained from the parent, we obtained a blood sample from each participant. Additionally, saliva samples were collected from parents. Participation of both parents was not required for our analysis [12]. These samples were used to obtain DNA for genotyping. Demographic and clinical data were abstracted from medical records. The study protocol was approved by the Baylor College of Medicine Institutional Review Board. **Table 1.** Summary of 128 Tagging Single NucleotidePolymorphisms.

Gene	Chromosome	Number of Tagging SNPs
MTHFR	1	11
MTR	1	16
MTHFD2	2	4
MTRR	5	13
BHMT2	5	4
BHMT	5	7
DHFR	5	2
NOS3	7	6
FOLH1	11	5
FOLR2	11	2
MTHFD1	14	16
SHMT1	17	8
TYMS	18	8
CBS	21	14
SLC19A1	21	4
TCN2	22	8

doi: 10.1371/journal.pone.0084658.t001

SNP Selection and Genotyping Methods

Sixteen genes in the folate metabolic pathway (Table 1) were selected because of their role in DNA synthesis, repair, and methylation. Previous literature was also used in our selection strategy [14,16]. Tagging SNPs for the 16 genes were selected using an r^2 threshold of 0.80 and the MultiPop-TagSelect Algorithm (due to the multi-ethnic composition of the study population) in the Genome Variation Server, which utilizes information from multiple HapMap populations [17,18]. [17]SNPs with minor allele frequencies of <10% were not included in the analysis due to the sample size. Based on these criteria, 128 SNPs were available for analysis.

DNA was extracted from peripheral blood lymphocytes and saliva using the QIAmp DNA Blood Mini Kit (Qiagen, Valencia, CA) according to the manufacturer's protocol. Genotyping was done using the Sequenom MassARRAY iPLEX platform (Sequenom, San Diego, CA) in the Human Genetics Center at The University of Texas School of Public Health according to the manufacturer's instructions.

Statistical Analysis

SSGS was used to analyze the ALL case-parent triad data. SSGS was specifically designed to model genetic case-parent triad data because it combines the conditional logistic regression to model the likelihood of allele transmission from parents to a diseased child with a Bayesian hierarchical model to incorporate genetic structure in variable selection [6].

Data Preparation and Post Processing. To prepare data for analysis using SSGS, we used SimWalk2 [19] to obtain the most likely haplotypes from linkage format data. Maximum likelihood estimators and the covariance matrix of conditional logistic regression coefficients were computed using the *clogit* command of Stata to provide necessary components for Metroppolis-Hastings sampling within SSGS. We used a

modified C/C++ program SSGS [6] to sample from posterior distributions; where we modified the software to incorporate SNP data. The Markov chain output from SSGS was analyzed using the R package Bayesian output analysis (boa) [20] to obtain posterior inference and assess the convergence and stationarity of Markov chains.

Prior Distributions. We used a hierarchical prior distribution with two levels to model variable selection: one level for selecting genes and a second level for selecting SNPs within a gene. We assigned both the prior probability of including a gene as 0.5. These values for prior probability of inclusion have been shown to control well for both false positives and false negatives [6,9,10]. These prior settings also have the interpretation that every gene has a 50% chance of being associated with the disease and every SNP within a selected gene has a 50% chance of being associated with the disease. The prior distributions of regression coefficients were independent normal distributions with mean 0. The prior settings were chosen to best control for both false positives and false negatives [9].

SSGS Analysis. The SSGS analysis proceeded in two steps. In step 1, we performed SNP screening using SSGS within each chromosome. The 16 genes in the folate metabolism pathway reside on 10 different chromosomes (Table 1). Since LD typically does not span across chromosomes, we first performed independent SSGS analyses for the SNPs on each chromosome. Any SNPs with posterior probability of inclusion greater than 0.2, corresponding to Bayes factor greater than 0.75, proceeded to step 2. We used this threshold for posterior probability of inclusion, recognizing that we wanted to include as many SNPs in the second step as possible, even if the posterior evidence is mildly in favor of noninclusion. In step 2, all the SNPs selected from step 1 were analyzed simultaneously to identify SNPs associated with childhood ALL. Posterior inference, including odds ratios (ORs) and their 95 percent credible intervals (95% Cls), were calculated for SNPs with Bayes factor greater than 1. For each SSGS analysis, we ran two chains with different initial values for 600.000 iterations and used the last one-third iterations of two chains for pooled posterior inference. All the Markov chains passed the Geweke convergence diagnostic and the Heidelberger-Welch test for stationary using R package boa. In addition, two chains from different initial values for each analysis had high correlations, indicating convergence to the same posterior distribution.

Results

The population characteristics of childhood ALL cases included in our study were summarized in Table 2. There were 118 cases recruited from Texas Children's Cancer Center from 2003 to 2010, including 65 males and 53 females. For the study period, the participation rate was 85%. Of the 118 families, 36% were complete triads, however, based on previous assessments this is unlikely to bias the results [12]. The study included individuals of all racial/ethnic groups, 59 non-Hispanic whites, 6 non-Hispanic blacks, 46 Hispanics, and

Table 2. Population characteristics of childhood acute lymphoblastic leukemia cases, Texas Children's Cancer Center, 2003-2010.

Characteristic	No. (%)		
Triads included	118		
Case sex			
Male	65 (55.0)		
Female	53 (45.0)		
Race/ethnicity			
Non-Hispanic White	59 (50.0)		
Non-Hispanic Black	6 (5.1)		
Hispanic	46 (39.0)		
Other	7 (5.9)		
Age (range 0-14 years)			
<4 years	56 (47.4)		
4-7 years	46 (39.0)		
>7 years	16 (13.6)		

10.1371/journal.pone.0084658.t002

Table 3. SNPs Selected from Initial Screening.

		PPI* from chromosomal	Bayes factor from joint
Gene	SNP	analysis (Phase 1)	analysis (Phase 2)
MTHFD2	rs1667627	0.335	0.341
MTHFD2	rs12196	0.227	0.268
BHMT2	rs670220	0.245	0.576
BHMT2	rs682985	0.449	0.580
BHMT2	rs557302	0.405	0.311
NOS3	rs3918186	0.854	7.381
SLC19A1	rs1051266	0.216	1.926

Posterior probability of inclusion.

doi: 10.1371/journal.pone.0084658.t003

7 belonging to other racial/ethnic groups. All the cases were under 14 years old when recruited.

We analyzed 128 tagging SNPs of 16 folate metabolic genes to identify SNPs associated with childhood ALL. The SNPs with posterior probability of inclusion greater than 0.2 in the initial screening within each chromosome proceeded to the final analysis. In the initial screening, 7 SNPs among the 128 tagging SNPs were identified, 2 SNPs in gene MTHFD2, 3 SNPs in gene BHMT2, 1 SNP in gene NOS3, and 1 SNP in gene SLC19A1 (Table 3).

In the final analysis of 7 selected SNPs from initial screening. NOS3 rs3918186 and SLC19A1 rs1051266 had Bayes factors greater than 1 (Table 4). In other words, the posterior odds of including the two SNPs in the model were greater than the prior odds of including the two SNPs, indicating that our data supported the association between the two SNPs and childhood ALL risk. Specifically, NOS3 rs3918186 had a Bayes Factor of 7.38, whereby for each copy of the minor allele, there was a 2.16 times risk of developing childhood ALL (OR = 2.16; 95% CI: 1.51-3.15) [21]. We found less evidence in our data for SLC19A1 rs1051266 being associated with childhood ALL. For

Discussion

To our knowledge, this is the first application of Bayesian hierarchical models designed for case-parent triads to identify SNPs associated with disease. Previous assessments utilizing this approach have explored microsatellite markers [6]. We extended this method to include the evaluation of SNPs because of the availability of high-dimensional SNP array data for many phenotypes and as case-parent triads are becoming more common in the role of inherited genetic variation on childhood cancer risk [15,22-25]. The case-parent triad design provides an advantage to the traditional case-control design as it is immune to population stratification bias. This is because analyses are based on whether the inheritance of alleles by affected children deviates from Mendelian expectation rather than a comparison of genotypes between a case group and a control group [12,13]. Additionally, the case-parent triad design is useful when appropriate controls are difficult to identify or enroll. Finally, family-based designs often provide greater power than traditional case-control designs [26].

In our study, we used SSGS to analyze 128 tagging SNPs in 16 folate metabolic genes to identify associations with childhood ALL risk. Using Bayes factors among this variants in childhood ALL case-parent triads, two SNPs were identified with a Bayes factor greater than 1. There was evidence that the minor alleles of *NOS3* rs3918186 and *SLC19A1* rs1051266 were positively associated with childhood ALL according to commonly cited guidelines for Bayes Factors [21]. In fact, the minor alleles of each of these SNPs carried twofold increase in risk for childhood ALL.

Endothelial nitric oxide synthase 3 (NOS3) is responsible for the production of nitric oxide (NO), which modulates homocysteine concentrations by inhibition of 5methyltetrahydrofolate-homocysteine methyltransferase, the enzyme that synthesizes methionine from homocysteine and 5mTHF [27]. *NOS3* rs3918186 is an intronic variant [28]. Nitric oxide and oxidative stress have been suggested as potential mechanisms of childhood leukemogenesis [14,16,23,29,30]. To our knowledge, this variant has not been assessed in relation to childhood ALL.

The gene *SLC19A1* encodes for reduced folate carrier 1 (RFC-1), which is a transmembrane protein that transports folate across cell membranes, thereby influencing folate levels. The G80A (rs1051266, G>A) polymorphism in RFC-1 is associated with altered folate/antifolate levels [31,32]. While, to our knowledge, *SLC19A1* rs1051266 has not been evaluated for childhood ALL risk, it has been associated with colorectal cancer [33] and prostate cancer [34]. However, a recent assessment by Metayer et al. evaluating *SLC19A1*, as well as other genes in the folate pathway, used a tagging SNP approach found no association with SNPs in *SLC19A1* and childhood ALL [16].

The major limitation of this study is the sample size (n = 118), which did not allow us to detect modest associations. In

Table 4. Two SNPs Identified from Final Analysis.

Gene	SNP	Odds ratio	95% CI	PPI [*]	Bayes factor
NOS3	rs3918186	2.16	(1.51, 3.15)	0.711	7.38
SLC19A1	rs1051266	2.07	(1.25, 3.46)	0.391	1.93

* Posterior probability of inclusion.

doi: 10.1371/journal.pone.0084658.t004

fact, based on this sample size, with a minor allele frequency of 10% (our minor allele frequency inclusion criteria for SNPs), α =0.05, β =0.8, and assuming a log-additive model of inheritance, we had the power to detect an odds ratio of 2.12 based on power calculations using Quanto Version 1.2.5 [35-37]. Our SNP selection strategy may have also affected our ability to identify associations, as we limited our inclusion to those with a minor allele frequency of ≥10%. In other words, we were not able to discover disease associations due to rare variants. Additionally, we were not able to stratify our results by ALL subtypes (e.g., B-lineage or T-lineage), as this information was not available, or age at diagnosis. However, in spite of these limitations, we were able to identify significant associations between folate metabolic variants and childhood ALL using SSGS. An important strength of our study was the use of the case-parent triad design. Additionally the use of SSGS allowed for the control for multiple comparisons [9], which is important as we evaluated 128 SNPs.

Our findings are suggestive of the role of inherited genetic variation in the folate metabolic pathway on childhood ALL risk. We believe they also suggest the utility of Bayesian variable selection methods in the context of case-parent triads for evaluating the role of SNPs on disease risk, especially under the circumstances of smaller sample sizes. We identified two potential inherited effects that were undetected in our previous study [15]. Our findings suggest that SSGS can be used to incorporate LD information to identify disease associated SNPs and to appropriately estimate the relative risk coefficients through averaging the posterior distributions [6,10]. Additionally, as we evaluated 128 SNPs, the use of the priors used here have been shown to control for false positive findings in simulation studies [9]. The use of Bayes factors offers a way to summarize the strength of evidence in our data for specific SNPs [21], allowing us to prioritize future follow-up investigations. Overall, SSGS provides a useful approach to investigate genetic factors associated with early onset diseases such as childhood ALL.

Acknowledgements

The authors would like to thank Ms. Megan Grove-Gaona for her technical assistance and the families who participated in this study.

Author Contributions

Conceived and designed the experiments: PJL MES MDS. Performed the experiments: MES. Analyzed the data: YC MDS

PJL. Contributed reagents/materials/analysis tools: YC MDS DN MES. Wrote the manuscript: PJL YC MES.

References

- Sherborne AL, Hemminki K, Kumar R, Bartram CR, Stanulla M et al. (2011) Rationale for an international consortium to study inherited genetic susceptibility to childhood acute lymphoblastic leukemia. Haematologica 96: 1049-1054. doi:10.3324/haematol.2011.040121. PubMed: 21459794.
- Vijayakrishnan J, Houlston RS (2010) Candidate gene association studies and risk of childhood acute lymphoblastic leukemia: a systematic review and meta-analysis. Haematologica 95: 1405-1414. doi:10.3324/haematol.2010.022095. PubMed: 20511665.
- Papaemmanuil E, Hosking FJ, Vijayakrishnan J, Price A, Olver B et al. (2009) Loci on 7p12.2, 10q21.2 and 14q11.2 are associated with risk of childhood acute lymphoblastic leukemia. Nat Genet 41: 1006-1010. doi: 10.1038/ng.430. PubMed: 19684604.
- Sherborne AL, Hosking FJ, Prasad RB, Kumar R, Koehler R et al. (2010) Variation in CDKN2A at 9p21.3 influences childhood acute lymphoblastic leukemia risk. Nat Genet 42: 492-494. doi:10.1038/ng. 585. PubMed: 20453839.
- Treviño LR, Yang W, French D, Hunger SP, Carroll WL et al. (2009) Germline genomic variants associated with childhood acute lymphoblastic leukemia. Nat Genet 41: 1001-1005. doi:10.1038/ng.432. PubMed: 19684603.
- Swartz MD, Kimmel M, Mueller P, Amos CI (2006) Stochastic search gene suggestion: a Bayesian hierarchical model for gene mapping. Biometrics 62: 495-503. doi:10.1111/j.1541-0420.2005.00451.x. PubMed: 16918914.
- Chipman HA, George EI, McCulloch RE (2001) The practical implementation of Bayesian model selection. Model Selection. Beachwood, OH: Institute of Mathematical Sciences.
- George EI, McCulloch RE (1993) Variable Selection Via Gibbs Sampling. Journal of the American Statistical Association 88: 881-889. doi:10.1080/01621459.1993.10476353.
- Swartz MD, Shete S (2007) The null distribution of stochastic search gene suggestion: a Bayesian approach to gene mapping. BMC Proc 1 Suppl 1: S113. doi:10.1186/1753-6561-1-s1-s113. PubMed: 18466454.
- Swartz MD, Yu RK, Shete S (2008) Finding factors influencing risk: comparing Bayesian stochastic search and standard variable selection methods applied to logistic regression models of cases and controls. Stat Med 27: 6158-6174. doi:10.1002/sim.3434. PubMed: 18937224.
- Swartz MD, Peterson CB, Lupo PJ, Wu X, Forman MR et al. (2013) Investigating multiple candidate genes and nutritents in the folate metabolism pathway to detect genetic and nutritional risk factors for lung cancer. PLOS ONE 8: e53475. doi:10.1371/journal.pone.0053475. PubMed: 23372658.
- Weinberg CR (1999) Allowing for missing parents in genetic studies of case-parent triads. Am J Hum Genet 64: 1186-1193. doi: 10.1086/302337. PubMed: 10090904.
- Weinberg CR, Wilcox AJ, Lie RT (1998) A log-linear approach to caseparent-triad data: assessing effects of disease genes that act either directly or through maternal effects and that may be subject to parental imprinting. Am J Hum Genet 62: 969-978. doi:10.1086/301802. PubMed: 9529360.
- Koppen IJ, Hermans FJ, Kaspers GJ (2010) Folate related gene polymorphisms and susceptibility to develop childhood acute lymphoblastic leukaemia. Br J Haematol 148: 3-14. doi:10.1111/j. 1365-2141.2009.07898.x. PubMed: 19775302.
- Lupo PJ, Nousome D, Kamdar KY, Okcu MF, Scheurer ME (2012) A case-parent triad assessment of folate metabolic genes and the risk of childhood acute lymphoblastic leukemia. Cancer Causes Control 23: 1797-1803. doi:10.1007/s10552-012-0058-z. PubMed: 22941668.
- Metayer C, Scélo G, Chokkalingam AP, Barcellos LF, Aldrich MC et al. (2011) Genetic variants in the folate pathway and risk of childhood acute lymphoblastic leukemia. Cancer Causes Control 22: 1243-1258. doi:10.1007/s10552-011-9795-7. PubMed: 21748308.
- Carlson CS, Eberle MA, Rieder MJ, Yi Q, Kruglyak L et al. (2004) Selecting a maximally informative set of single-nucleotide polymorphisms for association analyses using linkage disequilibrium. Am J Hum Genet 74: 106-120. doi:10.1086/381000. PubMed: 14681826.
- National Heart L, and Blood Institute, (2010) GVS Genome Variation Server version 5.11

- Sobel E, Lange K (1996) Descent graphs in pedigree analysis: applications to haplotyping, location scores, and marker-sharing statistics. Am J Hum Genet 58: 1323-1337. PubMed: 8651310.
- 20. Smith B (2008) Bayesian Output Analysis Program (BOA) for MCMC. 1.17-2 ed
- 21. Kass RE, Raftery AE (1995) Bayes Factors. Journal of the American Statistical Association 90: 773-795. doi: 10.1080/01621459.1995.10476572.
- Nousome D, Lupo PJ, Okcu MF, Scheurer ME (2013) Maternal and offspring xenobiotic metabolism haplotypes and the risk of childhood acute lymphoblastic leukemia. Leuk Res 37: 531-535. doi:10.1016/ j.leukres.2013.01.020. PubMed: 23433810.
- Infante-Rivard C, Vermunt JK, Weinberg CR (2007) Excess transmission of the NAD(P)H:quinone oxidoreductase 1 (NQO1) C609T polymorphism in families of children with acute lymphoblastic leukemia. Am J Epidemiol 165: 1248-1254. doi:10.1093/aje/kwm022. PubMed: 17332311.
- Lupo PJ, Nousome D, Okcu MF, Chintagumpala M, Scheurer ME (2012) Maternal variation in EPHX1, a xenobiotic metabolism gene, is associated with childhood medulloblastoma: an exploratory case-parent triad study. Pediatr Hematol Oncol 29: 679-685. PubMed: 22994552.
- Spector LG, Ross JA, Olshan AF (2013). Children's Oncology Group's 2013 blueprint for research: Epidemiology. Pediatr Blood Cancer 60: 1059-1062.
- Ott J, Kamatani Y, Lathrop M (2011) Family-based designs for genome-wide association studies. Nat Rev Genet 12: 465-474. doi: 10.1038/nrg2989. PubMed: 21629274.
- Brown KS, Kluijtmans LA, Young IS, Woodside J, Yarnell JW et al. (2003) Genetic evidence that nitric oxide modulates homocysteine: the NOS3 894TT genotype is a risk factor for hyperhomocystenemia. Arterioscler Thromb Vasc Biol 23: 1014-1020. doi:10.1161/01.ATV. 0000071348.70527.F4. PubMed: 12689917.
- Genome Variation Server (2010); GVS Genome Variation Server, version 5.11
- Lightfoot TJ, Johnston WT, Painter D, Simpson J, Roman E et al. (2010) Genetic variation in the folate metabolic pathway and risk of childhood leukemia. Blood 115: 3923-3929. doi:10.1182/ blood-2009-10-249722. PubMed: 20101025.
- Margolin JF, Rabin KR, Steuber CP, Poplack DG (2011) Acute Lymphoblastic Leukemia. In: PA PizzoDG Poplack. Principles and practice of pediatric oncology. Philadelphia: Lippincott Williams & Wilkins. pp. 518-565.
- Białecka M, Kurzawski M, Roszmann A, Robowski P, Sitek EJ et al. (2012) Association of COMT, MTHFR, and SLC19A1(RFC-1) polymorphisms with homocysteine blood levels and cognitive impairment in Parkinson's disease. Pharmacogenet Genomics 22: 716-724. doi:10.1097/FPC.0b013e32835693f7. PubMed: 22890010.
- 32. Dervieux T, Furst D, Lein DO, Capps R, Smith K et al. (2004) Polyglutamation of methotrexate with common polymorphisms in reduced folate carrier, aminoimidazole carboxamide ribonucleotide transformylase, and thymidylate synthase are associated with methotrexate effects in rheumatoid arthritis. Arthritis Rheum 50: 2766-2774. doi:10.1002/art.20460. PubMed: 15457444.
- Levine AJ, Lee W, Figueiredo JC, Conti DV, Vandenberg DJ et al. (2011) Variation in folate pathway genes and distal colorectal adenoma risk: a sigmoidoscopy-based case-control study. Cancer Causes Control 22: 541-552. doi:10.1007/s10552-011-9726-7. PubMed: 21274745.
- 34. Collin SM, Metcalfe C, Zuccolo L, Lewis SJ, Chen L et al. (2009) Association of folate-pathway gene polymorphisms with the risk of prostate cancer: a population-based nested case-control study, systematic review, and meta-analysis. Cancer Epidemiol Biomarkers Prev 18: 2528-2539. doi:10.1158/1055-9965.EPI-09-0223. PubMed: 19706844.
- Gauderman W, Morrison J (2006) A computer program for power and sample size calculations for genetic-epidemiology studies.
- Gauderman W, Morrison J (2006) QUANTO 1.1: A computer program for power and sample size calculations for genetic-epidemiology studies, <u>http://hydra.usc.edu/gxe</u>.
- Gauderman WJ (2002) Sample size calculations for matched casecontrol studies of gene-environment interaction. Stat Med 21: 35-50. doi:10.1002/sim.973. PubMed: 11782049.