JOURNAL OF CLINICAL ONCOLOGY

Gene Expression Profiling for Survival Prediction in Pediatric Rhabdomyosarcomas: A Report From the Children's Oncology Group

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Submitted November 24, 2008; accepted October 30, 2009; published online ahead of print at www.jco.org on February 1, 2010.

Supported in part by Grants No. U01-CA-114757 from the Strategic Partnering to Evaluate Cancer Signatures (SPECS) program (T.J.T.) and No. U10 CA98543 from the Children's Oncology Group Chair, National Cancer Institute, National Institutes of Health, Bethesda, MD.

Authors' disclosures of potential conflicts of interest and author contributions are found at the end of this article.

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0732-183X/10/2807-1240/\$20.00

DOI: 10.1200/JCO.2008.21.1268

Purpose

We investigated whether tumors from diagnostic biopsies of primary rhabdomyosarcoma (RMS) contain relevant prognostic information in the form of gene expression signatures that can be used to model and predict outcome of patients.

Patients and Methods

A 22,000-probe set microarray was used to evaluate 120 RMS specimens and correlate gene expression patterns to survival. Multivariate gene expression models or metagenes were developed using cross-validated Cox regression proportional hazards modeling and were evaluated using Kaplan-Meier analysis.

Results

A 34-metagene, based on expression patterns of 34 genes, was highly predictive of outcome. It was not highly correlated with individual clinical risk factors such as patient age, stage, tumor size, or histology. However, it was correlated with a risk classification used by the Children's Oncology Group and the biologic subsets of alveolar histology tumors.

Conclusion

These data support further evaluation of RMS metagenes to discriminate patients with good prognosis from those with poor prognosis, with the potential to direct risk-adapted therapy.

J Clin Oncol 28:1240-1246. © 2010 by American Society of Clinical Oncology

INTRODUCTION

The cure rate for patients with rhabdomyosarcoma (RMS) is more than 70% for patients with nonmetastatic disease,¹ and much of this realized gain over the past few decades can be attributed to the use of intensive multimodal therapy including surgery, radiotherapy, and chemotherapy. This cure rate is not expected to change significantly until targeted tumor-specific agents are developed. Because multimodal therapy can be associated with acute toxicities and long-term adverse effects, such as growth and developmental defects, one of the major areas for improvement relates to quality of life for young cancer survivors.² Recent studies have revealed that some patients can be treated effectively without radiotherapy³ and with less intensive chemotherapy,⁴ reducing acute and long-term adverse effects.5 Moreover, there appear to be subsets of patients with metastatic disease at diagnosis with an atypically more favorable outcome.6,7

A crucial determinant of the overall success of such risk-adapted therapy is the effectiveness of

clinical staging systems for patient prognosis and treatment assignment. Various forms of clinicopathologic staging have been used to define risk in several international clinical trial groups over the past several decades, and the latest development used in ongoing clinical trials of the Children's Oncology Group (COG; under the auspices of the COG Soft Tissue Sarcoma Committee) is a three-tier risk classification system. The COG risk classification system incorporates both of the earlier postsurgical clinical group and TNM stage schemes as well as tumor histology,⁸ and it appears to be the most powerful prognostic scheme devised to date.⁹

One issue with the COG risk classification system is that many patients fall into the intermediate-risk category where survival is most heterogeneous,¹⁰ suggesting that even the best clinical risk model has difficulty in identifying some aspects of underlying biology of tumors, in particular relating to their clinical aggressiveness.¹¹ Molecular staging using, for example, gene expression profiles has promise in predicting long-term patient outcome by analysis of the tumor at diagnosis.¹² An inherent assumption of this approach, supported by recent analyses^{13,14} is the hypothesis that every tumor contains informative gene expression signatures that, at the time of diagnosis, can predict the biologic behavior of the tumor over time.¹⁵ A powerful approach for modeling patient survival data is using Cox regression proportional hazards models; recently, this has been applied to gene expression data sets^{11,16-18} in efforts to generate true continuous predictors of survival that are independent of clinicopathologic variables in predicting treatment outcome.¹¹ In this proof-of-concept study, we describe the development of a metagene or multivariable continuous predictor of outcome using Cox regression–based modeling for 120 patients with RMS.

PATIENTS AND METHODS

Tumor Specimens

Tumor specimens used to develop outcome prediction models were, as recently reported,¹⁹ obtained from the Intergroup Rhabdomyosarcoma Study Group (IRSG)/Pediatric Cooperative Human Tissue Network (Columbus, OH) and Childrens Hospital Los Angeles (CHLA) institutional tumor banks from 120 patients who were enrolled in IRSG IV and V COG clinical trials. Clinical covariates were obtained from the COG Statistics and Data Center (Arcadia, CA). Two patients had mixed alveolar/embryonal histology and were considered alveolar for the purposes of this analysis. From the previously reported study, we selected only those patients with RMS histology (alveolar, embryonal, spindle-cell, and botryoid) on review diagnosis (ie, excluded all patients with non-RMS soft tissue sarcoma or undifferentiated sarcoma) and those with sufficient follow-up data (ie, alive [censored] patients with < 2 years of follow-up were omitted) for this analysis. Sample preparation and Affymetrix GeneChip Human U133A (Affymetrix, Santa Clara, CA) microarray protocols were previously described.^{19,20} Complete microarray protocols can be found at the University of Southern California (USC)/CHLA Genome Core Web site at http://genomecore-chla.usc.edu/GenomeCore/GenomeCore/II.

Analysis of Gene Expression

All data management and analysis was conducted using the Genetrix suite of tools for microarray analysis (Epicenter Software, http://www .epicentersoftware.com). Probe set modeling and data preprocessing were derived using the robust multi-array algorithm implemented within the ProbeProfiler module (Corimbia, Berkeley, CA). The full data set of 22,215 probe sets was reduced to 21,718 probe sets (henceforth, genes) by eliminating genes with a standard deviation of less than 10 Affymetrix difference intensity

Affymetrix ID	Gene Name	Gene Symbol		
Genes correlated to good patient outco	ome			
214643_x_at	Bridging integrator 1	BIN1		
219953_s_at	Chromosome 11 open reading frame 17	C11orf17		
218314_s_at	Chromosome 11 open reading frame 57	C11orf57		
201905_s_at	CTD (carboxy-terminal domain, RNA polymerase II, polypeptide A) small phosphatase-like	CTDSPL		
204643_s_at	Ecto-NOX disulfide-thiol exchanger 2	ENOX2		
218695_at	Exosome component 4	EXOSC4		
207688_s_at	Inhibin, beta C	INHBC		
222250_s_at	Integrator complex subunit 7	INTS7		
202788_at	Mitogen-activated protein kinase-activated protein kinase 3	МАРКАРКЗ		
213946_s_at	Obscurin-like 1	OBSL1		
35156_at	R3H domain and coiled-coil containing 1	R3HCC1		
218392_x_at	Sideroflexin 1	SFXN1		
207069_s_at	SMAD, mothers against DPP homolog 6 (Drosophila)	SMAD6		
214662_at	WD repeat domain 43	WDR43		
219548_at	Zinc finger protein 16 (KOX 9)	ZNF16		
Genes correlated to poor patient outco	ome			
221588_x_at	Aldehyde dehydrogenase 6 family, member A1	ALDH6A1		
211248_s_at	Chordin	CHRD		
210656_at	Embryonic ectoderm development	EED		
212546_s_at	FRY-like 1	FRYL		
209525_at	Hepatoma-derived growth factor, related protein 3	HDGFRP3		
220447_at	Histamine receptor H3	HRH3		
209184_s_at	Insulin receptor substrate 2	IRS2		
204075_s_at	KIAA0562	KIAA0562		
204584_at	L1 cell adhesion molecule	L1CAM		
213672_at	Methionine-tRNA synthetase	MARS		
215921_at	Nuclear pore complex interacting protein-like 1	NPIPL1		
209791_at	Peptidyl arginine deiminase, type II	PADI2		
205632_s_at	Phosphatidylinositol-4-phosphate 5-kinase, type I, beta	PIP5K1B		
211974_x_at	Recombination signal binding protein for immunoglobulin kappa J region	RBPJ		
218394_at	Rogdi homolog (Drosophila)	ROGDI		
213437_at	RUN and FYVE domain-containing 2; Run- and FYVE-domain containing protein	RUFY3		
219196_at	Secretogranin III	SCG3		
213434_at	Syntaxin 2	STX2		
 202342_s_at	Tripartite motif-containing 2	TRIM2		

units of a normalized data range, and the data were log transformed. The complete tumor microarray data set (including sample covariate data) can be found on the National Cancer Institute (NCI) Cancer Array Database at https://array.nci.nih.gov/caarray/project/trich-00099.

Metagene Construction and Evaluation

Metagenes were constructed as previously described,²⁰ using Cox proportional hazards modeling of RMS gene expression data under crossvalidation. Genes were ranked and selected using sampling statistics obtained across multiple iterations testing for significance in both training (n = 60) and testing (n = 60) randomized subsets. Weighting factors were obtained from the signed square root of the Cox χ^2 test statistic modeled on the entire cohort. The metagene score for each patient was calculated as a weighted sum of the gene expression value. Detailed descriptions of the data analysis can be found in the Data Supplement (online only).

Survival Analysis

Comparison of survival times was carried out using Kaplan-Meier survival plots and log-rank tests of significance. Comparisons between molecular groups and tests of association used Fisher's exact or χ^2 tests to compare the frequency distributions of patient characteristics. Multivariate tests for association of factors with survival used a Cox regression proportional hazards model.

RESULTS

Generation of Multigene Prognostic Models

A cohort of 120 pediatric RMS patient tumor samples (Supplementary Table 1, online only) with at least 2 years censored follow-up data after diagnosis (except patients who died of disease at any time point) were used to identify genes correlated to overall survival (OS) times with Cox proportional hazards regression modeling. Most of the deaths (67%) occurred within the first 2 years of diagnosis and the cause of death was attributed to the tumor in all patients except for two (one from infection on regimen and one from toxicity unrelated to the chemotherapy regimen). Of the patients who died, 24 (62%) had alveolar histology, 13 (33%) had embryonal histology, and two (5%) had mixed alveolar/embryonal histology. No reported deaths occurred in patients with spindle-cell or botryoid histology tumors.

Using Cox modeling of OS with log-transformed gene expression data (see Patients and Methods), 578 genes with significant Cox χ^2 scores over 2,500 iterations of the algorithm (P < .01) were identified (Supplementary Table 2, online only). Next, multigene continuous predictors of outcome were assembled and evaluated as described previously²⁰ (see schematic in Appendix Fig A1, online only). The maximum likelihood estimate of the χ^2 test statistics were determined for each multivariate model and showed that a 34-probe set model or 34-metagene (MG34; Table 1) had the highest significance score (blue curve, Appendix Fig A1). By permuting the gene expression data and generating new metagenes from the permuted data set, we show that permuted models do not reach statistical significance, indicating that these results are not likely due to chance alone (red curve, Appendix Fig A2, online only).

Post Hoc Analysis of MG34

To validate the performance of the MG34, RMS patients were split into three groups (tertiles, determined by the histogram bar groupings) by their computed metagene predictor scores (Fig 1A). The mean metagene predictor scores for the third tertile were five- and 17-fold greater than second and first tertile patient scores, respectively. Kaplan-Meier analysis revealed that patients in the first (n = 39; blue



Fig 1. Metagene predictor scores determine outcome in rhabdomyosarcoma patients. (A) Histogram showing the binned distribution of the 34-metagene predictor scores for 120 patients (vertical purple lines highlight the tertile cut points). Kaplan-Meier survival analysis of all 120 rhabdomyosarcoma patients (B) using tertiles as groups and (C) for 113 RMS patients with known Children's Oncology Group (COG) risk groups (Table 2). Numbers below the curves indicate the number of patients at risk, and *P* values are from log-rank test. Int, intermediate.

curve) and second (n = 41; green curve) tertiles had 5-year OS rates of 98% and 75%, respectively (Fig 1B). In contrast, patients in the third tertile (n = 40; red curve) had a 5-year OS rate of only 29% and median survival of 24 months. Of the cohort of 120 patients, there

COG Risk Group	Risk Group Criteria	5-Year OS, (%)*	No. of Patients in MG34 Tertiles		
			1st	2nd	3rd
Low	Embryonal histology and stage 1 or stage 2/3, group I/II	90	19	11	2
Intermediate	Embryonal histology and stage 2/3, group III or alveolar histology, groups I-III	77	12	22	14
High	All patients with group IV disease	24	5	7	21
			5-Year OS (%)*		2/e
			95	76	29

were seven patients for whom missing stage or clinical group data meant that we could not classify them into the risk groups now used by the COG (in current clinical trials for RMS). The remaining 113 patients were grouped according to the COG risk groups as indicated in Table 2. Kaplan-Meier analysis (Fig 1C) shows that the 5-year OS rates for patients in this cohort grouped according to the COG risk category criteria are reflective of the survival rates observed in larger cohorts from COG clinical trials.¹⁰ We also observed that MG34 tertile groups are highly correlated to COG risk groups; for example, most high-risk patients are found in the third tertile, whereas few clinically low-risk patients are within this tertile (Table 2).

Next, we looked at the predictive value of the MG34 tertiles within the COG risk groups. COG low-risk patients (n = 32) were mostly in the MG34 first tertile (n = 19) or second tertile (n = 11)except for two embryonal histology (stage 3, group II disease) patients who were categorized in the third tertile (log-rank P < .013). While the log-rank test for the comparison of survival is < 0.05, it is mostly the result of early failure of one of these patients in the third tertile (Fig 2A). For intermediate-risk patients (n = 48), there appears to be clear evidence that the MG34 tertiles are predictive of survival (Fig 2B). For COG intermediate-risk group patients in the MG34 first tertile, the 5-year OS rate was 100% (n = 12), whereas second tertile (n = 22) and third tertile (n = 14) patients had 5-year OS rates of 86% and 43%, respectively (log-rank P < .00003). Of note, we observed that 71% (12 of 17) of COG intermediate-risk patients with tumors expressing the PAX3-FKHR fusion gene were in the MG34 third tertile, the one that is most different in terms of survival. In contrast, six of seven PAX7-FKHR and three of three fusion-negative alveolar histology tumors from the COG intermediate-risk group were in the MG34 second tertile (Supplementary Table 3, online only). Therefore, it appears that for intermediate-risk patients, higher MG34 scores (eg, third tertile) are tightly correlated to the PAX3-FKHR alveolar subtype (Supplementary Table 4, online only). For patients in the COG high-risk group, 64% (21 of 33) were in the MG34 third tertile. Five patients with group IV disease (four embryonal, one alveolar) and improved survival were categorized into the first tertile, but for the remainder of these patients, there was no appreciable difference in the survival curves between the second MG34 tertile (n = 7) and the third MG34 tertile (n = 21), except median survival was 33 months versus 22 months, respectively (Fig 2C). Comparison of the metagene predictor scores with clinical risk factors can be found in Supplementary Table 5 (online only). Appendix Figure A3 (online only) shows the distribution of MG34 scores within histologic and genetic subtypes.

DISCUSSION

Previous gene expression profiling of RMS patient tumors by our group and by others¹⁹⁻²² focused primarily on resolving issues of diagnosis and enhancing the understanding of tumor classification from a genome-wide perspective. While a 2006 study²⁰ showed that expression signatures of putative PAX-FKHR target genes may be of prognostic value in the subset of PAX-FKHR translocation-positive alveolar RMS patients and a 2009 report¹⁹ showed differences in prognosis for molecular-based classes of RMS tumors, these findings have not yet had an impact on clinical practice for patient stratification or assignment to treatment protocols. The main reason is that they do not seem to add much more prognostic information beyond that captured by established pathologic criteria, such as favorable (ie, embryonal) versus unfavorable (ie, alveolar) tumor histology, known for nearly three decades as an independent prognostic factor. The MG34 described here appears to discriminate patient risk independent of tumor histology and, as a continuous rather than discrete variable, it reflects the spectrum of differential gene expression observed in this heterogeneous group of tumors.

Genes such as *L1CAM* that are highly expressed in poor-outcome patients, a cell adhesion molecule,²³⁻²⁵ and *IRS2*²⁶ are associated with increased metastatic potential and invasiveness in several tumor types. Another poor-outcome gene, transcription factor *RBPSJ*, is involved in repression of differentiation in numerous cancers.²⁷ Conversely, a good-outcome gene, *BIN1*, is a well-characterized tumor suppressor gene that promotes muscle differentiation²⁸ and differentiation of tumor cells.²⁹ Though the functional relationship of MG34 genes in determining tumor behavior and hence outcome of RMS patients is at present unclear, these and many others (Supplementary Table 2) appear to impart independent prognostic information. In addition, we have shown that the MG34 model is one of numerous expression signatures correlated to patient prognosis (Appendix Fig A2), as has been demonstrated in other tumor systems.^{30,31}

We previously reported a PAX-FKHR 33-metagene that predicted outcome in a subset of alveolar RMS patients whose tumors expressed products of PAX-FKHR fusion genes. This PAX-FKHR 33-metagene and the present pan-RMS MG34 do not show any overlap. This is not surprising given the fact that the PAX-FKHR metagene was generated from a list of putative PAX-FKHR targets derived from expression analysis of an in vitro model system (ectopic expression of



Fig 2. Evaluation of metagene predictor scores within Children's Oncology Group (COG) risk groups. Kaplan-Meier survival analysis of COG low-risk (A), intermediate-risk (B), and high-risk (C) patients using 34-metagene tertiles as groups. Numbers below the curves indicate the number of patients at risk, and *P* values are from loo-rank test.

PAX-FKHR in ERMS RD cell lines) and PAX-FKHR-positive primary tumors only. However, five genes (MYLPF, TNNC2, IL4R, NELL1, and BMP5) from the cell line model system analysis were also identified in the present analysis of outcome-correlated genes in all RMS tumors (Supplementary Table 2) though they were not incorporated into the MG34 model reported here. Our working hypothesis is that PAX3 and PAX7 (and their cognate PAX-FKHR fusion genes in alveolar RMS) activate a unique transcriptional program that confers rhabdomyosarcoma-ness in general (eg, myogenic phenotype in a sarcoma). Furthermore, the PAX-FKHR fusion proteins in alveolar RMS are believed to further activate a transcriptional program that confers a more aggressive phenotype (perhaps in part characterized by some of the genes identified here and in the 2006 study). Previous work from the Barr group³² demonstrated that levels of PAX-FKHR are also crucial where PAX-FKHR overexpressed in cell lines caused transformation at lower levels and growth suppression at higher levels. Multiple functionally significant splice forms of PAX-FKHR may have implications for tumor phenotypes such as clinical aggressiveness and the correlation between fusion gene expression; wild-type PAX3/7 expression and other factors yet to be identified likely have important roles in conferring different biologic properties to RMS cells.³²⁻³⁵ In a follow-on study now underway on a larger cohort of RMS patients with higher resolution exon microarrays, we intend to address the question of whether RMS patient survival can be better modeled with separate metagenes for PAX-FKHR and fusion-negative RMS.

Kaplan-Meier analysis of the objectively derived MG34 tertiles shows patients divided into three highly disparate groups in terms of survival, which suggests that MG34 tertiles are predictive of survival. Additionally, MG34 tertiles are correlated with the COG clinicopathologic risk category used to assign patients with RMS to treatment studies. This is perhaps not surprising because both depend on features related to the biology of the tumors, although they are measured in different ways. All but two of the patients who were low risk by clinicopathologic features had tumors classified into the first or second MG34 tertiles. Most had embryonal disease, and survival did not appear to differ significantly by whether low-risk patients were in the first or second tertile. Most patients (21 of 33) who are high risk by clinicopathologic features had tumors classified into the third MG34 tertile. Patients in the COG intermediate-risk group had tumors evenly distributed across the MG34 tertiles. Poorer survival outcomes were observed for third-tertile patients within the COG intermediaterisk group, with the majority of these patients (12 of 14) having PAX3-FKHR and alveolar histology disease. The poorest prognosis MG34 third tertile appears to be associated with PAX3-FKHR alveolar histology disease; overall, 63% (25 of 40) of the MG34 third-tertile patients have PAX3-FKHR alveolar tumors, whereas the percentages are only 3% (one of 39) and 10% (four of 41) for the first and second tertiles, respectively. In contrast, 73% (eight of 11) of PAX7-FKHR alveolar histology tumors were in the second tertile, supporting previous studies that report a more favorable outcome for this subset of alveolar patients.33,36

While the third tertile predominately comprised the less favorable PAX3-FKHR alveolar RMS tumors, it also included eight patients with embryonal disease and two with mixed alveolar/embryonal disease. Intriguingly, the metagene tertile risk groups varied most markedly in patients who presented with metastatic disease (group IV), which is the most adverse prognostic factor for RMS patients.⁶ While most of the metastatic disease patients were found in the third tertile group, nearly a third were found in the other two tertiles and, in accordance with previous observations, these (8 of 11) had primarily group IV embryonal histology tumors.^{6,37} These data suggest that a genomic-based classifier such as MG34 could be used to discern patients with high-risk disease who are most responsive to current therapeutic modalities and may provide a means to separate them from high-risk patients unlikely to respond to conventional chemotherapy regimens. This approach could therefore enable clinicians to better test experimental therapeutic agents on chemotherapynaïve high-risk patients⁹ and make testing clinical trials for these agents more efficient.

Current methods for RMS staging have evolved to direct riskadapted therapy⁹ using complex clinical risk models.³⁸ This is important not only for patient management but also for evaluation of the effects of different treatment regimens in clinical trials. However, it appears that clinicopathologic-based staging systems do not identify many of the fundamental differences in underlying tumor biology.¹¹ The MG34, a continuous predictor of patient outcome when split into tertile groups, performed similarly to the COG risk groups in a training cohort. This is notable since the MG34 risk groups were derived from statistical cut points (ie, tertile groups) and were not optimized by post hoc analysis. Further work is required to expand genome-wide analyses to further training and independent validation cohorts, efforts that will likely require hundreds of patient samples as has been done previously for analysis of other prognostic factors on routine clinical material (eg, formalin-fixed paraffin embedded tumor sections).^{7,22} The present work suggests that the focus should be on the intermediate-risk patients, the most prevalent type of RMS clinical trial patients. In this subgroup, the MG34 model appears to add prognostic information and separates out significant numbers of patients with more favorable or worse prognosis than the OS trends in this heterogeneous risk category. On the basis of these initial results, genomic classifiers for prognosis and the substratification of patients

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at the time of diagnosis have great promise as clinical tools to better the treatment, management, and outcomes for RMS patients.

AUTHORS' DISCLOSURES OF POTENTIAL CONFLICTS OF INTEREST

Although all authors completed the disclosure declaration, the following author(s) indicated a financial or other interest that is relevant to the subject matter under consideration in this article. Certain relationships marked with a "U" are those for which no compensation was received; those relationships marked with a "C" were compensated. For a detailed description of the disclosure categories, or for more information about ASCO's conflict of interest policy, please refer to the Author Disclosure Declaration and the Disclosures of Potential Conflicts of Interest section in Information for Contributors.

Employment or Leadership Position: Elai Davicioni, GenomeDx Biosciences (C); Jonathan D. Buckley, Epicenter Software (C) **Consultant or Advisory Role:** None **Stock Ownership:** Elai Davicioni, GenomeDx Biosciences; Jonathan D. Buckley, Epicenter Software **Honoraria:** None **Research Funding:** None **Expert Testimony:** None **Other Remuneration:** None

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