

# The Measurement of Comorbidity by Cancer Registries

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**Abstract:** The goals of this current research were to demonstrate the feasibility of cancer registrars at different hospitals to collect comorbidity information and to demonstrate the impact of comorbidity on cancer statistics.

This was a prospective observational study of 11,906 newly diagnosed cancer patients, of whom detailed demographic, tumor, and follow-up information was available for the first consecutive 8,550.

The most frequent comorbidity was hypertension (40.2%), followed by previous solid tumor (12.4%) and diabetes (12.2%). There was a near even distribution of comorbidity severity (None, Mild, Moderate, and Severe) and it differed significantly across the participating centers. There was a significant prognostic impact of comorbidity on survival. At any point in time, patients with more severe levels of comorbidity had worse survival. For the entire cohort, the adjusted hazard ratio (95% CI) for comorbidity was: Mild 1.1 (0.9,1.2), Moderate 1.3 (1.1, 1.5), and Severe 1.9 (1.7, 2.2).

In this study, we demonstrated the feasibility of cancer registrars to collect comorbid health information and the value of this information to cancer statistics.

**Keywords:** cancer statistics, comorbidity, prognosis

## Introduction

Comorbidity is an important aspect of the patient with cancer.<sup>1,3</sup> The presence of comorbid ailments and the severity of those ailments can impact on diagnosis, prognosis, treatment selection, and quality of cancer care. Comorbidities can impact on the diagnostic and therapeutic management of patients through changes in the utility of screening for new cancers in asymptomatic patients and diagnosis of cancer in symptomatic patients. The use of preferred antineoplastic therapy might be contraindicated for some patients due to the presence of comorbid ailments. Comorbidity may also impact on the accurate assessment of the effectiveness of two or more competing treatments. Extermann et al<sup>4</sup> and Firat et al<sup>5</sup> found that comorbidity and functional status are independent predictors of outcome in patients with cancer and recommend that both be included in clinical trials and other studies. In their report entitled, *Measuring Quality of Cancer Care*, the National Cancer Policy Board, Institute of Medicine, and the National Research Council<sup>6</sup> identified the measurement and reporting of comorbidity as an important element for national

cancer registry systems. For these reasons, many authors have advocated for the inclusion of comorbidity in cancer statistics.<sup>4,7-12</sup>

Instruments to measure the severity of comorbidity can be classified based on the origin of the data – primary data vs. secondary data. Primary data are collected directly from physicians, nurses, other health care professionals, or through medical record review. Examples of instruments that use primary data are the Kaplan-Feinstein Index,<sup>13</sup> the Charlson Co-Morbidity Index,<sup>14</sup> and the Index of Co-Existent Disease.<sup>15</sup> Secondary data are derived from administrative and financial databases maintained by hospitals, insurance companies, and state and federal governments. Included in the group of comorbidity measures that rely on secondary data are the Dartmouth-Manitoba,<sup>16</sup> the Deyo adaptations of the Charlson Co-Morbidity Index,<sup>17</sup> and more recently developed Comprehensive Prognostic Index by Fleming and colleagues.<sup>18</sup>

The Surveillance, Epidemiology, and End Results (SEER) Program of the National Cancer Institute (<http://seer.cancer.gov/AboutSEER.html>) is the most authoritative source of information on

cancer incidence and survival in the United States.<sup>19</sup> Started in 1973, SEER now contains information on over 2.5 million Americans. The National Cancer Data Base (NCDB) is a nationwide oncology outcomes database that was founded as a joint project of the Commission on Cancer (COC) of the American College of Surgeons (ACOS) and the American Cancer Society (ACS). The NCDB includes over 1500 hospitals in 50 states and is in its 10th year of operation.<sup>20</sup> At present, neither SEER nor NCDB collect comorbid health information routinely, although SEER included comorbid health information in special studies and projects<sup>21,22</sup> and NCDB plans to include comorbidity in upcoming lung and gastric cancer Patient Care Evaluation projects.

The goals of this research are to demonstrate the feasibility of cancer registrars at different types of cancer hospitals collecting comorbidity information as a part of their usual chart abstraction process, and to demonstrate the impact of comorbidity on cancer statistics.

## Methods

### Study Design

This was a prospective observational study.

"The Measurement of Comorbidity by Cancer Registries"

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Submitted: 02/20/02. Accepted: 12/28/02.

### Definition of Comorbidity

Comorbidity assessment was performed through a review of the medical records and other health information sources that the registrars use to obtain the COC-required data elements. Individual comorbid ailments and overall level of comorbidity were collected and defined according to the *Adult Comorbidity Evaluation-27* form and Coding Book.<sup>23</sup> The *Adult Comorbidity Evaluation (ACE-27)* is a new 27-item comorbidity index for use with cancer patients. The ACE-27 grades specific diseases and conditions into one of three groups, Grade 1, Grade 2, or Grade 3, according to the severity of organ decompensation and prognostic impact. Once the patient's individual diseases or comorbid conditions are classified, an Overall Comorbidity Score, *None*, *Mild*, *Moderate*, or *Severe*, is assigned based on the highest ranked single ailment. In the cases where 2 or more Grade 2 ailments occur in different organ systems or disease groupings, the Overall Comorbidity Score should be designated as *Severe*. All participating cancer registrars had participated in a formal comorbidity education program and were certified to code comorbidity accurately.

### Population Under Study

The population consisted of all newly diagnosed (analytic) cancer patients presenting to one of the 6 participating hospitals of the Comorbidity Network between July 1999 and July 2002. The Clinical Outcomes Research Office has received comorbidity data, as reported by the ACE-27 (*Adult Comorbidity Evaluation-27*) form, for 11,906 cancer patients. Of these 11,906 patients, the office has received, at the time of this publication, detailed demographic, tumor, and follow-up information for the first, consecutive 8550 patients.

### Collection of Data

The participating hospitals forwarded the completed ACE-27 forms to the Outcomes Office every 4-8 weeks. These forms are stored in locked cabinets until sufficient numbers are reached for electronic entry. The ACE-27 forms are then electronically entered into an EXCEL<sup>®</sup> (Microsoft Corporation, Redmond, WA) data file by International Data Corporation (St. Louis, MO), a professional data entry company. This information was then transferred from EXCEL to ACCESS<sup>®</sup> (Microsoft Corporation, Redmond, WA) for data management, clean up, and verification.

The Outcomes Office has coordinated the electronic transfer of tumor registry information for 8550 patients from the participating centers. The tumor registry information contained variables defined and coded according to the Commission on Cancer (COC) ROADS manual.<sup>24</sup> Individual patients were identified through unique tumor accession numbers assigned by the participating centers. The Clinical Outcomes Office did not receive patient name or other identifying information (ie, social security number). The ACE-27 comorbid health information was linked, through the unique tumor accession number, with the demographic, tumor, and follow-up information.

### Statistical Analysis

Standard descriptive statistics (eg, proportions and percentiles) were used to describe the population, the incidence of comorbid ailments, and survival outcomes. Cross-tabulation was used to explore the frequency distribution of the 4 levels of comorbidity across the hospitals. To test whether the observed differences were statistically significant, a chi-square ( $\chi^2$ ) test of significance was used and significance was established at the  $p < 0.05$  level (2-tailed). The prognostic impact of comorbidity was explored through the use of life survival analysis and the generation of Kaplan-Meier survival curves. The log-rank test<sup>25</sup> was used to assess the significance of survival differences across comorbidity levels. The independent prognostic impact of comorbidity, controlling for the impact of age, gender, race, and morphologic extent of tumor, was assessed using Cox Proportional Hazards analysis.<sup>26</sup> The  $\chi^2$  statistic for the analysis of 2 separate models was used. The first model includes only the covariates age, gender, race, and stage of tumor. The second model includes comorbidity along with the important covariates. The difference in the  $\chi^2$  between the covariate model alone and the model containing covariates and comorbidity provides a measure of the independent statistical significance of comorbidity. The prognostic discriminatory capacity of all models is presented by the c statistic, or concordance index.<sup>27,28</sup> Discrimination refers to the ability of the model to separate those who live from those who die. The c-statistic measures predictive information derived from a set of predictor variables in a model. When the outcome of interest is a binary event (dead/alive) the c-statistic is calculated by considering all possible pairs of patients, at least one of whom has

died. The index is the proportion of such pairs with the dead patient being the one predicted to die and the other having a higher predicted probability of survival. Hanley and McNeil<sup>29</sup> demonstrated that the c-statistic is identical to the area under a "receiver operating characteristic" (ROC) curve, a widely used measure of diagnostic discrimination. The c-statistic ranges from 0.5 to 1.0; a value of 0.5 indicates random predictions and a value of 1 indicates perfect identification of patients who die from patients who survive. A model with a c-statistic value greater than 0.8 has some utility in predicting the response of individual patients.<sup>30</sup> The c-statistic can also be computed for survival analysis or censored data. If the predicted survival time is larger for the patient who lived longer, the predictions for that pair are said to be concordant with the outcomes. Computation of the c-statistic for survival analysis is conveniently available as a STATA automatic do file (stcstat). All statistical analyses, except calculation of the c-statistic, were performed using SAS software, version 8.2 (SAS Institute, Cary NC).

Human studies approval for this study was obtained at Washington University and each of the participating centers. Participating centers were selected because of their interest in the comorbidity assessment. Centers received \$1 for completed ACE-27 forms and \$3 per patient for electronic transfer of demographic, tumor, and follow-up information from the Clinical Outcome Office.

### Results

The names and descriptions of the 6 hospitals participating in the Nationwide Comorbidity Network are shown in Table 1. The hospitals included 2 teaching hospitals and 4 community hospitals. The number of registrars at each hospital ranged from 1 to 9 and the number of cases abstracted between July 1999 and July 2001 ranged from 572 to 5658.

The feasibility of collecting comorbidity information by cancer registrars at different hospitals was evaluated in previous research.<sup>23</sup> In Table 2, suggested attributes or characteristics that could be used to measure the feasibility of comorbidity data collection are provided. In that research<sup>23</sup>, the percent agreement between registrars coding overall severity from standardized medical records ranged from 88% to 100%. The degree of agreement beyond what would be expected by chance (kappa

**Table 1.** Description of Hospitals Participating in Nationwide Comorbidity Network

Name, Location of Hospital	COC Designation	# of Registrars	# of Patients
Barnes-Jewish Hospital St. Louis, MO	Teaching Hospital Cancer Program	9	5658
Dakota Clinic Fargo, ND	Community Hospital Cancer Program	4	1983
North Kansas City Hospital Kansas City, MO	No COC designation	1	1717
Washington Hospital Center Washington, D.C.	Teaching Hospital Cancer Program	2	1045
Queen of the Valley Hospital Napa, CA	Community Hospital Cancer Program	1	931
Hannibal Regional Hospital Hannibal, MO	Community Hospital Cancer Program	1	572
			11,906 Total

**Table 2.** Attributes and Characteristics to Measure the Feasibility of Comorbidity Data Collection

Attribute/Characteristic	Results of Cancer Comorbidity Education Program <sup>23</sup>
Can registrars be trained to code comorbidity?	Yes
Degree of ease to train registrars to code comorbidity?	Very; 1 day inservice required
How much time does it take, on average, to identify comorbid ailments and code them?	2.1 minutes/per chart, although this increase was not statistically different from coding without comorbidity
Are cogent comorbid health data/information available to the registrar at the time of chart abstraction?	Yes
How reliable is the collection process?	Very reliable
How valid is the identification of comorbid ailments and the description of severity?	Very
How comparable is the comorbidity data across different hospitals?	Very comparable since medical record systems are standardized
How stable are the definitions of comorbidity and descriptions of severity across time? What is the impact of new technology on both identification of disease and prognostic implications?	Unknown
How easy is it to incorporate comorbidity data collection into electronic tumor registry system? How easy is it to incorporate comorbidity information into hospital cancer statistic reports?	Very easy. Hospitals placed overall comorbidity score (0,1,2,or 3) into 'user-defined' field in their hospital-based tumor registry. Comorbidity information is easily analyzed and reported in hospital cancer statistic reports

statistic) was quite high immediately after the training program and remained very good 6 months later. The registrars also demonstrated that they were able to achieve high degrees of accuracy (sensitivity and specificity) in their coding of overall comorbidity. The cancer registrars documented the time to abstract medical record information for 42 charts without comorbidity and 42 different charts with comorbidity. The mean time ( $\pm$ SD), in minutes, for chart abstraction without comorbidity was 35.9 (17.2) and with comorbidity was 38.0 (16.8). The mean difference was 2.1 minutes, indicating that the time for abstraction with comorbidity was slightly longer, on average, than coding without comorbidity, although this difference was not statistically significant. When asked the question, "How difficult and burdensome, on average, is coding comorbidity in relation to what is usually coded for a chart?" the registrars answered either *Slightly* difficult or *Not At All*. When asked, "How time consuming, on average, is coding comorbidity in relation to what is usually coded for a chart?" the majority responded *Slightly* or *Not At All*. One cancer registrar commented, "Comorbidity is no problem!"

The most frequent comorbidity was hypertension (40.2%), the second most frequent was previous solid tumor (12.4%), and the third most frequent was diabetes (12.2%). (Table 3) Interestingly, lymphoma, pancreatic conditions, leukemia, and paralysis occurred in less than 0.5% of the cohort. The distribution of overall comorbidity severity (*None*, *Mild*, *Moderate*, and *Severe*) across the 6 participating centers is shown in Figure 1. As can be seen, there is a consistent distribution of all 4 levels of severity of comorbidities within each hospital. The actual distribution of comorbidity severity level differed significantly across the centers ( $\chi^2 = 650.6$ ;  $p < 0.0001$ ).

Of the 11,906 patients with completed ACE-27 information, the Outcomes Office received tumor registry information on the first consecutive 8550 patients. The description of the population of patients for whom complete linked data was available is shown in Table 4. As can be seen, the population consisted of older patients (50.6% greater than age 65), mostly (82.5%) white, and equally divided between male and female. The percentage of patients with *Moderate* or *Severe* comorbidity was 30.6%. A large number (33.5%) of patients had localized

**Table 3.** Prevalence of Comorbidities in 8550 Cancer Patients

Comorbid Condition	N	%
Hypertension	3437	40.2
Solid tumor*	1064	12.4
Diabetes mellitus	1046	12.2
Pulmonary	1016	11.9
Angina	910	10.6
Myocardial Infarction	596	7.0
Arrhythmias	504	5.9
Gastrointestinal	364	4.3
Psychiatric	355	4.2
Congestive heart failure	338	4.0
Stroke	324	3.8
Obesity	230	2.7
Alcohol abuse	198	2.3
Peripheral vascular disease	182	2.1
Venous disease	175	2.1
Renal	164	1.9
Rheumatologic	157	1.8
Liver	132	1.5
Dementia	101	1.2
Neuromuscular	92	1.1
AIDS	49	0.6
Illicit Drugs	35	0.4
Lymphoma	24	0.3
Pancreas	22	0.3
Leukemia	20	0.2
Paralysis	13	0.2

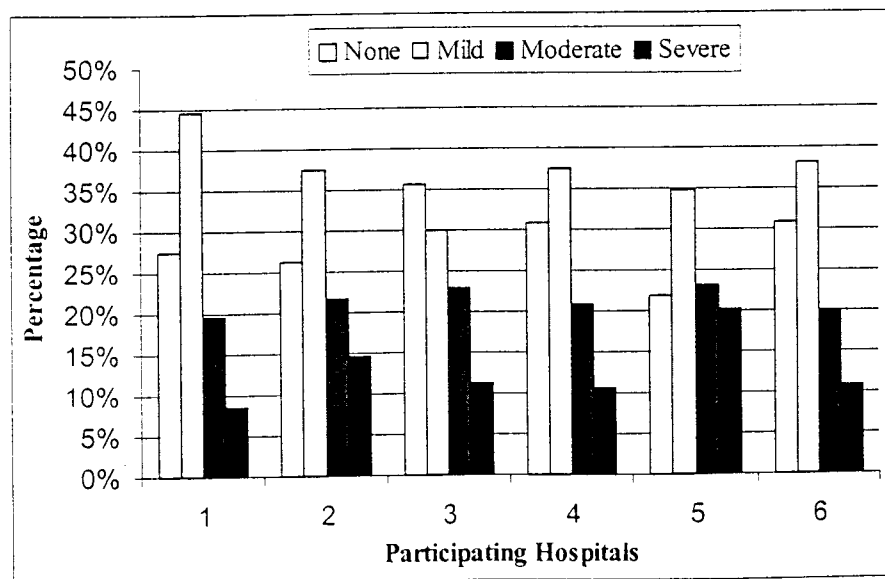
\* includes only invasive lesions

tumors, while 34.6% had regional or distant spread of their tumor at the time of diagnosis. The most frequent cancer sites were Prostate (18.1%), Breast (16.1%), Lung (14.2%), and Colorectal Cancer (13.1%)(Table 5).

The prognostic impact of comorbidity on survival is shown in Figure 2. As can be seen, there is a strong prognostic impact of comorbidity on survival (Log Rank  $\chi^2 = 326.34$ ;  $p < 0.0001$ ). At any

point in time, patients with more severe levels of comorbidity had worse survival. The prognostic impact of comorbidity overall and within specific tumor sites was analyzed using Cox Proportional Hazards models (Table 6). Each of these models was adjusted by age, gender, race, and stage of tumor. The prognostic impact of *Mild*, *Moderate*, and *Severe* comorbidity (relative to *None*) is shown for the entire cohort (All Cancers) and for the 6 most common cancer sites in this study. For the entire cohort, the adjusted hazard ratio (95% confidence interval) for *Mild* is 1.1 (0.9,1.2), *Moderate* 1.3 (1.1, 1.5), and *Severe* 1.9 (1.7, 2.2). This relationship between level of comorbidity and survival is statistically significant ( $\chi^2 = 3272.3$ ;  $p < 0.0001$ ). For all individual cancer sites, there is a distinct prognostic gradient based on severity of comorbidity — the adjusted mortality risk increases with increasing levels of comorbidity. The prognostic accuracy baseline models without comorbidity and models with comorbidity is explored further through evaluation of model performance and discrimination. As shown in Table 7, the addition of comorbidity to the baseline model of demographics and TNM Stage alone results in a statistically significant increase in model performance overall and for patients in all cancer sites. For all models except lung, the c-statistic description of discrimination was 0.79 or greater, indicating moderate to excellent predictive strength of the mathematical models.

**Figure 1.** The Distribution of Comorbidity Severity Across 6 Hospitals Participating in the Nationwide Comorbidity Network, N=11,906 Patients ( $\chi^2 = 650.6$ ;  $p < 0.0001$ )



**Table 4.** Description of the Nationwide Comorbidity Network Patient Population, N = 8550

Variable	Category	N(%)
Age Group	≤50	1383 (16.2)
	50-64	2847 (33.3)
	65-74	2400 (28.1)
	75+	1920 (22.5)
Race	White	7057 (82.5)
	Black	1367 (16.0)
	Other	126 (1.5)
Gender	Male	4349 (50.9)
	Female	4201 (49.1)
Comorbidity Level	None	2656 (31.1)
	Mild	3284 (38.4)
	Moderate	1664 (19.5)
	Severe	946 (11.1)
TNM Stage*	In Situ	526 (6.2)
	Stage 1	2334 (27.3)
	Stage 2	2732 (32.0)
	Stage 3	1318 (15.4)
	Stage 4	1640 (19.2)

\*Combination of TNM pathologic and TNM clinical.

## Discussion

In this study, the feasibility of cancer registrars collecting comorbid health information, as well as the value of this information to cancer statistics is demonstrated. The registrars at the participating centers were trained to code comorbidity as part of a National Cancer Institute-sponsored education program. Since completion of this education program, the registrars continue to code comorbidity from medical record review. The registrars are able to derive sufficient information from the medical record to generate a comorbidity score. As previously reported,<sup>23</sup> registrars stated that little additional time was required to collect comorbidity data. On average chart abstraction with comorbidity was 2.1 minutes longer than chart abstraction alone. The registrars were polled and none felt, in their circumstances, that the additional time to collect these data was burdensome. These findings confirm the early findings at Barnes-Jewish Hospital<sup>31</sup> and validate the inclusion of comorbidity in cancer registries.

The distribution of comorbidity severity varied across the 6 centers. For example, the percentage of patients with severe comorbidity in Hospital 5 was approximately twice the percentage as

in Hospital 1. As a part of the training program, one of the authors (AJB) traveled 3 times to each of the training centers. During these visits she evaluated the quality of the medical records at each of the institutions. It was her opinion that the quality of the medical records and availability of comorbid health data was relatively similar across the hospitals. High reliability in the coding of comorbidity among registrars at different hospitals was also documented. Therefore, it can be concluded that the differences in overall comorbidity across the institutions reflect true differences in comorbidity and are not an artifact. It was also found that overall survival was related to the levels of comorbidity severity. For all patients, the prognostic impact of comorbidity remained significant even after controlling for the patient's age, gender, race, and stage of tumor.

The inclusion of comorbidity in cancer registries has attracted attention and been advocated by several national organizations. The National Cancer Policy Board of the Institute of Medicine stated that the inclusion of comorbidity is important for the assessment of the quality of cancer care.<sup>9</sup> At the Annual Veteran's Administration Meeting for

**Table 5.** Distribution of Tumor Sites, N = 8550

Tumor Site	N(%)
Prostate	1545 (18.1)
Breast (Female)	1378 (16.1)
Lung (Non-Small Cell)	1215 (14.2)
Colorectal	1120 (13.1)
Gynecological	685 (8.0)
Head and Neck	388 (4.5)

Cancer Coding (October 5, 2000, Washington, DC), one of the co-authors (AJB) presented this study to representatives of the VA hospitals around the country. The Cancer Advisory Board of the United Kingdom National Health Service has decided to add comorbidity information to the UK National Cancer Core Dataset (Report available at [http://www.nhsia.nhs.uk/cancer/pages/dataset/docs/cdp\\_lessons\\_learned\\_comorbidity.pdf](http://www.nhsia.nhs.uk/cancer/pages/dataset/docs/cdp_lessons_learned_comorbidity.pdf)) The Commission on Cancer has mandated the collection of comorbidity and complication information, using the ICD-9-CM system, for inclusion in CoC-approved hospital-based cancer registries.

There is not one standard methodology for routine collection of comorbidity information. The methodology of collection will depend on the goals of the collection (ie, prognostic stratification, evaluation of treatment effectiveness, quality of care assessment), availability and format of the comorbidity information, education and training of the individuals charged with collection of the data, and analytical abilities of those individuals using the data. There are benefits and weaknesses for each approach.

As this and previous research<sup>23,31</sup> demonstrate, medical record extraction of comorbid health information by trained cancer registrars can be done accurately and efficiently from the medical record. Earlier research demonstrated that this effort could be accomplished with no additional time, since the registrars rely on the same data sources (eg, medical record) for the comorbidity information as for the required tumor, treatment, and follow-up information. The cancer registrars must first be trained to identify cogent comorbidities from the medical record and to code the overall severity. The authors developed a training program that was used to train registrars at the participating hospitals described in this report (available from author). The original training program required

approximately 2½ days to complete. As a result of the experience gained from this training program, it has been streamlined and now requires approximately 1 full day to complete. The authors developed a web-based cancer comorbidity education program (<http://cancercomorbidity.wustl.edu/index.html>) through grant support from the National Cancer Institute.

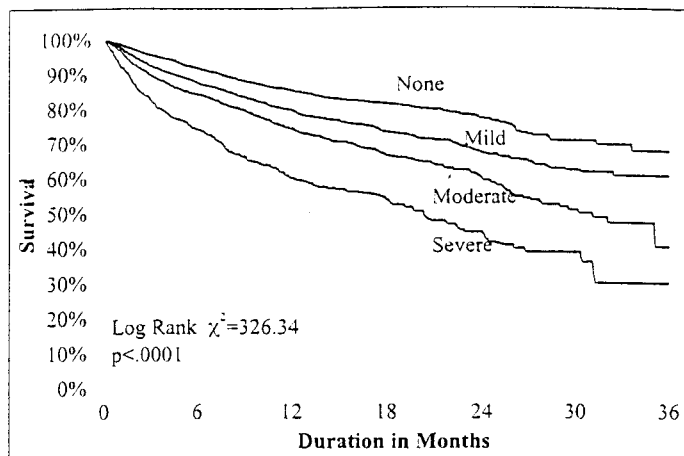
As part of the new *Facility Oncology Registry Data Standards* (FORDS) (<http://www.facs.org/dept/cancer/coc/fordsmanual.html>) process, cancer programs must report comorbidity and complication information from the hospital discharge "face sheet." The CoC requires that comorbid health information be defined as the first 6 discharge conditions from the inpatient medical record. Presumably, the NCDB will use a computer software package<sup>16,32</sup> to convert the ICD-9 diagnosis codes into an overall comorbidity score.

Unfortunately, there are several problems with the use of hospital administrative databases to assign levels of severity of comorbidity.<sup>33,34</sup> First, a significant number of cancer patients receive treatment as outpatients, and

thus may not have a discharge face sheet, or the face sheet may not reflect comorbidities since there is usually less documentation associated with these records. For example, Klabunde et al<sup>35</sup> found that less than 10% of patients with prostate or breast cancer from a national sample had comorbid conditions identified when only Medicare hospital

(Part A) claims were examined. By incorporating physician claims (Part B), the proportion of patients with comorbid conditions increased to 25%. Second, many registrars lack experience in the difference in coding philosophies between medical record technicians using ICD-9 codes and cancer registrars using ICD-O-3 codes. Third, many conditions that impact on treatment selection and prognosis for patients with cancer may not be included in the hos-

Figure 2. Impact of Comorbidity on Survival, N=8550



pital discharge summary because they do not impact on billing or other hospital administrative functions (eg, morbid obesity). Conversely, there are potentially thousands of different conditions and diagnoses that have ICD-9 codes, while only a finite (perhaps less than 30) number of comorbidities are important to the care of cancer patients. For many significant comorbid ailments, there are numerous ICD-9 codes that can lead to confusion and ambiguity. Because more

Table 6. Results of Cox Proportional Hazards Modeling: Impact of Comorbidity Severity on the Risk of Death by Specific Tumor Sites

Comorbidity Level	All Cancers N=8550 Adjusted Risk Ratio* <sup>†</sup> (95% CI) n	Prostate N=1545 Adjusted Risk Ratio* (95% CI) n	Breast N=1378 Adjusted Risk Ratio* (95% CI) n	Lung (Non Small Cell) N=1215 Adjusted Risk Ratio* (95% CI) n	Colorectal N=1120 Adjusted Risk Ratio* (95% CI) n	Gynecologic N= 685 Adjusted Risk Ratio* (95% CI) n	Head & Neck N=388 Adjusted Risk Ratio* (95% CI) n
None	Reference 2656	Reference 567	Reference 503	Reference 246	Reference 280	Reference 264	Reference 133
Mild	1.1 (0.9,1.2) 3284	1.1 (0.5,2.3) 664	1.4 (0.7,2.7) 510	1.1 (0.9,1.4) 465	1.2 (0.8,1.9) 425	0.7 (0.4,1.2) 247	0.6 (0.3,1.0) 150
Moderate	1.3 (1.1,1.5) 1664	2.9 (1.4,6.0) 236	2.7 (1.4,5.4) 243	1.1 (0.9,1.4) 302	1.7 (1.1,2.6) 254	1.1 (0.6,2.0) 115	1.3 (0.7,2.4) 69
Severe	1.9 (1.7,2.2) 946	7.6 (3.5,16.5) 78	4.3 (2.0,9.2) 122	1.6 (1.2,2.1) 202	2.2 (1.4,3.5) 161	2.0 (1.2,3.6) 59	1.4 (0.6,2.9) 36

\* Adjusted for age, gender, race, stage of tumor, and site<sup>†</sup>.

Table 7. Results of Cox Proportional Hazards Modeling: Impact of Comorbidity Severity on the Risk of Death by Specific Tumor Sites

Model Performance	All Cancers N=8550	Prostate N=1545	Breast N=1378	Lung (Non Small Cell) N=1215	Colorectal N=1120	Gynecologic N= 685	Head & Neck N=388
$\chi^2$ Demographics TNM Stage Alone	3173.6 $p < 0.0001$	121.6 $p < 0.0001$	89.6 $p < 0.0001$	333.2 $p < 0.0001$	257.9 $p < 0.0001$	142.7 $p < 0.0001$	74.7 $p < 0.0001$
Partial $\chi^2$ due to Comorbidity	98.7 $p < 0.001$	40.4 $p < 0.001$	19.2 $p < 0.001$	14.0 $p < 0.01$	16.7 $p < 0.001$	11.7 $p < 0.001$	11.1 $p < 0.01$
$\chi^2$ Demographics, TNM Stage, and Comorbidity	3272.3 $p < 0.0001$	162.04 $p < 0.0001$	108.8 $p < 0.0001$	347.2 $p < 0.0001$	274.6 $p < 0.0001$	154.4 $p < 0.0001$	85.8 $p < 0.0001$
c-statistic	0.85	0.89	0.84	0.71	0.81	0.84	0.79

\* Adjusted for age, gender, race, and stage of tumor. Reported  $\chi^2$  from log likelihood ratio.

than one code can sometimes be applied to a particular disease, different medical record technicians can assign different codes to the same comorbid condition. In some cases, these changes in coding have little impact on the patient's total comorbidity score, but for others these changes have an extreme impact on the patient's overall comorbidity.<sup>36</sup> ICD-9 codes reflect the presence of a particular condition but do not specify the level of physiological or clinical decompensation. This inability to code clinical severity decreases the value of the ICD-9 system for prognostic stratification research. Fourth, it is often difficult to distinguish complications from comorbidities when using hospital discharge records and ICD-9 codes. Finally, the use of ICD-9 codes to describe comorbidities will require that individual hospitals have conversion software to translate the specific ICD-9 codes into both text fields and an overall rating of comorbidity severity.

In conclusion, this paper demonstrates the ability of several hospitals to collect comorbidity information from the medical record. Comorbid health information is important for the care of patients with cancer and the interpretation of cancer statistics. The inclusion of comorbid health information, collected in a standard, valid, and time-efficient way by cancer registrars, can become an important new data element in cancer registries.

### Acknowledgements

Research supported through a grant from the NCI (R25 CA68304-04).

The authors would like to acknowledge the support and participation of the following registrars: Beverly Dunbar, ART, CTR, and Maida Herbst, Queen of the Valley Hospital, Napa, California; Suzanna S. Hoyler, CTR, Director, Oncology Clinical Information Center, Washington Cancer Institute, Washington Hospital Center; Tammy Wayne, RTT, Dakota Clinic, Fargo, North Dakota; Louanne Currence, RHIT, CTR, North Kansas City Hospital, North Kansas City, Missouri; Sheri Goodwin, RHIT, Hannibal Regional Hospital, Hannibal, Missouri.

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