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Understanding Health Care Costs in a Wisconsin Acute Leukemia Population

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Purpose We investigated factors driving health care costs of patients with a diagnosis of acute myeloid and acute lymphoblastic leukemia.

Methods Standard costs identified in insurance claims data obtained from the Wisconsin Health Information Organization were used in a sample of 837 acute leukemia patients from April 2009 to June 2011. The Andersen behavioral model of health care utilization guided selection of patient and community factors expected to influence health care costs. A generalized linear model fitting gamma-distributed data with log-link technique was used to analyze cost.

Results Type of treatment received and disease severity represented significant cost drivers, and patients receiving at least some of their treatment from academic medical centers experienced higher costs. Inpatient care and pharmacy costs of patients who received treatment from providers located in areas of higher poverty experienced lower costs, raising questions of potential treatment and medical practice disparities between provider locations. Directions of study findings were not consistent between different types of services received and underscore the complexity of investigating health care cost.

Conclusions While prevalence of acute leukemia in the United States is low compared to other diseases, its extreme high cost of treatment is not well understood and potentially influences treatment decisions. Acute leukemia health care costs may not follow expected patterns; further exploration of the relationship between cost and the treatment decision, and potential treatment disparities between providers in different socioeconomic locations, is needed. (*J Patient Cent Res Rev.* 2016;3:142-149.)

Keywords health care costs; acute leukemia cost; administrative data use

As the United States health care system works to control health care costs, it becomes increasingly important to understand the factors associated with high-cost care.[1] Exploring cost factors of low-prevalence but high-cost cancers is important to both identify and better understand underlying health care utilization patterns and cost. In 2007, Yu found the use of prolonged hospital care, high levels of medical technology and specialized health care services resulted in a high cost of treatment.[2] To achieve long-term survival, patients diagnosed with acute leukemia are expected to utilize diverse health care services.

Prior models of health care utilization have identified patient and community factors as determinants in the use of services.[3-5] Specifically, the Andersen behavioral model proposes that an individual's health care use can be attributed to individual and community or organizational factors that will either increase or decrease utilization.[4] Utilization factors are associated with biology (such as age and gender), social structure (such as education, occupation, ethnicity, environment and culture), and health beliefs (such as attitudes, values and knowledge). Furthermore, the availability of individual and community resources like income, insurance, transportation and diversity of services

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offered drive the use of health care. Finally, utilization may be influenced by the individual's perceived or evaluated need for these services as well as his or her ability to access health care resources, work within the health care system and effectively manage the clinical problem. Understanding cost factors of uncommon, high-cost cancers is important to patients, providers and communities impacted by these diseases.

This study investigated patient and community variables that may influence the cost of treatment for patients in Wisconsin diagnoses with acute myeloid leukemia or acute lymphoblastic leukemia. More specifically, this study sought to identify factors that may influence higher cost treatment of these two diseases.

METHODS

Data Source and Study Population

This study received approval from the University of Wisconsin-Milwaukee Institutional Review Board. Insurance claims data obtained from the Wisconsin Health Information Organization (WHIO) Datamart were used to identify a study population of 837 acute leukemia patients treated with chemotherapy alone or chemotherapy and hematopoietic stem cell transplant (HCT) from April 2009 to June 2011. WHIO is a statewide collaboration of insurance companies, health care providers, large employers and public agencies. Starting in 2005, this group developed a state-level database of health insurance claims in order to provide data useful for examining health care issues related to quality, efficiency and safety within the state of Wisconsin.[6] Access to the data is available through the WHIO Health Analytics Exchange, a database reporting system covering more than 247.6 million insurance claims for care to roughly 3.8 million Wisconsin residents. The exchange began collecting data in 2008 and provides access to a rolling 27 months of data, a total of 23.1 million episodes of care. Version 6 of the WHIO Datamart contains information for approximately 64.9% of Wisconsin's population. Commercial claims represent 42% of the total, 25% are Medicaid Fee-For-Service claims, 20% are Medicaid HMO claims, and 13% are Medicare claims. The active WHIO Datamart contains 24 months of insurance claims data collected over 27 months for completeness and refreshed approximately every 6 months.[6]

The study population included all patients with an ICD-9 diagnosis code of acute myeloid leukemia or acute lymphoblastic leukemia present in the WHIO database within the 2009–2011 timeframe. Claims costs were categorized and are presented as billed cost, paid cost and standard cost; standard cost is used in these analyses. Finkler previously identified the appropriate use of standard cost for studies with the perspective of actual operational cost or resources used.[7] WHIO calculates a standard cost variable to adjust for variations related to insurance contracting, region and disease severity and comorbidity, which is expected to provide a closer estimate of actual cost.

Design and Variables

This study is a cross-sectional secondary analysis of insurance claims data from the WHIO Datamart for patients with acute leukemia. With guidance from the Andersen model, study variables (Table 1) were included based on their expected influence on health care cost at the patient and community level.

Patient county and provider location percentage below poverty variables were calculated using WHIO data combined with U.S. Census data. Six cost criterion variables were analyzed separately: 1) total cost, 2) ancillary cost, 3) inpatient cost, 4) outpatient cost, 5) pharmacy cost, and 6) professional cost. Data were not consistently available for each cost criterion; therefore, while the total cost data set included all 837 patients, each analysis utilized only the data and corresponding population size available per cost criterion.

Statistical Analyses

Use of administrative databases in health care cost research is challenging due to the limitations of patient demographics, disruption in coverage, availability of clinical outcomes and censored data. Using prior literature as a guide, a generalized linear model (GLM) fitting gamma-distributed data with log-link technique was selected. Literature comparing GLMs for use in health economic analysis suggests the gamma log-link model as a candidate to provide a good fit for health care cost data, given its tendency for skewness, excess zeros and heavy right tails.[8-11] The final statistical model was selected after a comprehensive assessment of study data as

Table 1. Description of Study Variables

Variable	Behavioral model type	Measurement or range	WHIO DataMart
Leukemia diagnosis cost: ICD-9 code 204.xx ICD-9 code 205.xx	Criterion variable	Total Inpatient Outpatient Pharmaceutical Ancillary Professional	Cost = billed Cost = standard Service type: Ancillary = 1 Inpatient = 2 Outpatient = 3 Professional = 4 Pharmacy = 7 (does not include retail pharmacy claims)
Age	Predisposing characteristic	1–90 years	Age
Gender	Predisposing characteristic	0 = male 1 = female	Gender
Length of follow-up	Predisposing characteristic	1–25 months	End date of service to start date of service
Episode severity level	Need characteristic	1 = low 2 = low/medium 3 = high/medium 4 = high	Severity = highest level of severity coded
Treatment type	Need characteristic	0 = chemotherapy only 1 = chemotherapy and HCT	ICD code
Patient ZIP code; % of county below poverty level	Enabling resources	ZIP: 5-digit character; County poverty: continuous ratio	ZIP code; U.S. Census for % of all people below poverty level
Payer type	Enabling resources	0 = commercial 1 = public	Payer type = public payer coded when present
Provider type	Enabling resources	0 = community 1 = academic	Provider name
Provider ZIP code; % of ZIP below poverty level	Enabling resources	ZIP: 5 digit character; Provider ZIP poverty: %	ZIP code; U.S. Census for % of all people below poverty level

HCT, hematopoietic stem cell transplant.

well as for its ability to accommodate right-skewed data, the presence of zeros, differences in follow-up, many low-cost events versus few high-cost events, and overall fit considering model assumptions. The modified Park's test identified both Poisson and gamma family distributions as appropriate, given the cost criterion assessed, and visual inspection of residuals associated with raw and log-transformed data supported use of the log-link for approximating a normal distribution.

Modeling techniques used in this study ultimately produced estimates of predictor variable effect size (e^{β}), quantifying the magnitude of change in mean criterion value per 1-unit change in the predictor variable and offering the advantage of easier comparison and interpretation of differences between groups.[12-14] Each cost criterion variable was modeled to determine: 1) if a patient's predisposing characteristics (i.e. age, gender and length of follow-up), need for service factors (i.e. treatment type and episode severity), and enabling patient and community resources (i.e. percentage of residents in patient's county in poverty, payer type, provider type and percentage of residents in provider location in poverty) were predictive of cost; and 2) the magnitude of predictor variable influence on cost criterion variables. To identify variables that significantly influenced cost, each cost criterion was initially analyzed in a full model using all study variables. Table 2 provides the description of the final GLM gamma log-link models.

Variables for analysis in reduced models were identified in the GLM using a chi-squared test of the likelihood ratio with α of 0.05. Finally, a two-step hierarchical model was used to assess the influence of patient and community enabling variables over and above the influence of a patient's predisposing characteristics and need for services. This model began with the predisposing and need variables, then added the patient and community enabling variables.

RESULTS

Descriptive information of standard cost for each criterion variable is shown in Table 3. Mean standard cost varies greatly between criterion variables, for which inpatient costs were highest and ancillary costs lowest. Large differences were noted between mean and median cost, however, both follow similar direction.

Each significant full-model predictor variable also was significant in the reduced model. Only total cost was analyzed in the hierarchical model, and the results were the same as those of the reduced model. Reduced model results are presented as mean ratios and used a coefficient of variation, which represents the ratio of differences between groups as e^{β} (Table 4).

Table 2. Final GLM Gamma Log-Link Models

Variable
1. $E(Y_{Totalcost}) = exp(\beta_0 + \beta_1 lengthoffollow\text{-}up + \beta_2 age + \beta_3 gender + \beta_4 treatmenttype + \beta_5 severity + \beta_6 county\%belowpoverty + \beta_7 payertype + \beta_8 providertype + \beta_9 provider\%belowpoverty)$
2. $E(Y_{Ancillarycost}) = exp(\beta_0 + \beta_1 lengthoffollow\text{-}up + \beta_2 age + \beta_3 gender + \beta_4 treatmenttype + \beta_5 severity + \beta_6 county\%belowpoverty + \beta_7 payertype + \beta_8 providertype + \beta_9 provider\%belowpoverty)$
3. $E(Y_{Inpatientcost}) = exp(\beta_0 + \beta_1 lengthoffollow\text{-}up + \beta_2 age + \beta_3 gender + \beta_4 treatmenttype + \beta_5 severity + \beta_6 county\%belowpoverty + \beta_7 payertype + \beta_8 providertype + \beta_9 provider\%belowpoverty)$
4. $E(Y_{Outpatientcost}) = exp(\beta_0 + \beta_1 lengthoffollow\text{-}up + \beta_2 age + \beta_3 gender + \beta_4 treatmenttype + \beta_5 severity + \beta_6 county\%belowpoverty + \beta_7 payertype + \beta_8 providertype + \beta_9 provider\%belowpoverty)$
5. $E(Y_{Pharmacycost}) = exp(\beta_0 + \beta_1 lengthoffollow\text{-}up + \beta_2 age + \beta_3 gender + \beta_4 treatmenttype + \beta_5 severity + \beta_6 county\%belowpoverty + \beta_7 payertype + \beta_8 providertype + \beta_9 provider\%belowpoverty)$
6. $E(Y_{Professionalcost}) = exp(\beta_0 + \beta_1 lengthoffollow\text{-}up + \beta_2 age + \beta_3 gender + \beta_4 treatmenttype + \beta_5 severity + \beta_6 county\%belowpoverty + \beta_7 payertype + \beta_8 providertype + \beta_9 provider\%belowpoverty)$

Table 3. Description of Standard Costs

Cost criterion	N	Mean	Median	Standard deviation	Range	25% quartile	75% quartile
Total cost	837	43,379	2,723	102,703	10–1,228,960	539	35,471
Ancillary	164	4,123	1,230	8,834	5–64,248	296	3,248
Inpatient	232	80,787	40,908	104,001	2,680–836,656	16,855	107,750
Outpatient	639	8,410	1,953	17,590	10–227,957	493	9208
Pharmacy	390	17,078	5,070	60,012	1–1,097,437	483	17,434
Professional	748	6,491	1,002	11,379	7–80,867	298	7,448

Table 4. Estimated Reduced Model Summary Results for Standard Cost

Predisposing characteristics*	Reduced model standard claims cost					
	Total	**Ancillary**	**Inpatient**	**Outpatient**	**Pharmacy**	**Professional**
Age (decade)						
e^{β}	0.92	0.98	0.88	0.92	1.15	0.88
95% CI	0.87–0.96	0.97–1.002	0.83–0.93	0.88–0.97	1.07–1.23	0.84–0.91
P-value	0.007	0.08	<0.0001	0.002	<0.0001	<0.0001
Gender						
e^{β}	1.66			1.3		
95% CI	1.28–2.15			1.04–1.64		
P-value	0.0001			0.02		
Length of follow-up (months)						
e^{β}	1.03		0.98	1.06	1.03	1.08
95% CI	1.003–1.05		0.96–1	1.04–1.07	1.05–0.03	1.07–1.09
P-value	<0.0001		0.05	<0.0001	0.02	<0.0001
Need characteristics*	**Total**	**Ancillary**	**Inpatient**	**Outpatient**	**Pharmacy**	**Professional**
Treatment type						
e^{β}	0.14		0.3	0.19		0.22
95% CI	0.06–0.26		0.2–0.45	0.12–0.32		0.12–0.36
P-value	<0.0001		<0.0001	<0.0001		<0.0001
Severity level 1						
e^{β}	0.41	0.24	0.28	0.32	0.34	0.47
95% CI	0.26–0.61	0.07–0.95	0.17–0.49	0.20–0.51	0.17–0.67	0.34–0.67
P-value	0.0002	0.02	<0.0001	<0.0001	0.002	<0.0001
Severity level 2						
e^{β}	0.45	0.35	0.55	0.47	0.6	0.51
95% CI	0.34–0.61	0.19–0.66	0.41–0.74	0.34–0.66	0.39–0.93	0.41–0.63
P-value	<0.0001	0.001	<0.0001	<0.0001	0.02	<0.0001
Severity level 3						
e^{β}		0.32		0.64	0.59	
95% CI		0.17–0.61		0.44–0.92	0.35–0.96	
P-value		0.0004		0.02	0.03	
Enabling resources*	**Total**	**Ancillary**	**Inpatient**	**Outpatient**	**Pharmacy**	**Professional**
Provider type						
e^{β}	0.71	0.46	0.73	0.56	0.62	
95% CI	0.54–0.94	0.26–0.79	0.55–0.95	0.43–0.71	0.44–0.89	
P-value	0.018	0.005	0.02	<0.0001	0.01	
Provider % under poverty						
e^{β}				0.97	0.95	
95% CI				0.96–0.99	0.93–0.98	
P-value				<0.0001	0.002	

**Determinants in Andersen's model of health care utilization.*

CI, confidence interval; e^{β}, estimates of predictor variable effect size.

Total Cost

The average total cost for males was more than one and a half times the average total cost for females, and each additional month that a patient had claims present increased the average total cost by close to 2%. The average total cost of patients treated with only chemotherapy was 86% lower than the average total cost with both chemotherapy and HCT treatment. Patients with low illness severity (level 1) had a 59% lower average total cost than higher severity levels; patients with low- to mid-range severity (level 2) had a 55% less average total cost than higher levels of severity (3 and 4). Community provider's average total costs were 29% lower than average total costs of academic providers, and patients average total cost was 8% lower for every 10-year increase in patient age.

Ancillary Cost

The average ancillary cost of patients with low illness severity (level 1) was 76% lower than the average ancillary cost of patients with high severity level 4, patients with mid-range severity levels (levels 2 and 3) had 66% and 68% lower average ancillary costs than patients with high severity (level 4). Community provider average ancillary costs were 54% lower than the average ancillary cost of academic providers.

Inpatient Cost

The average inpatient cost of patients treated with only chemotherapy was 70% lower than the average inpatient cost of both chemotherapy and HCT treatment. Patients with low illness severity (level 1) had a 72% lower average inpatient cost than patients with high severity (level 4), and patients with mid-range severity (level 2) had a 45% lower average inpatient standard cost than those with high severity (level 4). Community providers had 27% lower average inpatient cost than academic providers. Average inpatient cost was reduced by 12% for every 10-year increase in patient age, and each additional month that a patient had claims increased the average inpatient cost by close to 2%.

Outpatient Cost

Males had 30% higher average outpatient cost compared to females, and each additional month that claims were present increased average outpatient cost by 5.5%. For each 10-year increase in age, average outpatient cost decreased by 7.6%. Patients treated with only chemotherapy had an 81% lower average outpatient cost than patients treated with both chemotherapy and HCT. Patients with low illness severity (level 1) had a 68% lower average outpatient cost than patients with high severity (level 4), patients with mid-range severity (level 2 or 3) had a 53% and 36% lower average outpatient cost, respectively, than those with high severity (level 4). Community providers had a 44% lower average outpatient cost than academic providers, and every 1% increase in the rate of poverty at the provider's location reduced average outpatient cost by 3%.

Pharmacy Cost

For each 10-year increase in patient age, average pharmacy cost decreased by 15%. Each additional month that claims were present increased average pharmacy cost by 3%. Patients with low illness severity (level 1) had a 66% lower average pharmacy cost than patients with high severity (level 4); patients with mid-range severity (level 2 or 3) had a 40% and 41% lower average pharmacy cost, respectively, than those with high severity (level 4). Cost for community providers was 38% lower than the average pharmacy cost of an academic provider, and every 1% increase in the provider location poverty rate reduced average pharmacy cost by 5%.

Professional Cost

Each additional month that a patient had claims present increased average professional cost by close to 8%. For each 10-year increase in age, average professional cost decreased by 12.5%. Patients treated with only chemotherapy had a 78% lower average professional cost than those treated with both chemotherapy and HCT. Patients with low illness severity (level 1) had a 53% lower average professional cost than patients with high severity (level 4), and patients with mid-range severity (level 2) had a 49% lower average professional cost than high-severity patients (level 4).

DISCUSSION

The objective of this study was to identify and better understand factors associated with use of health services specific to patients diagnosed with acute myeloid leukemia and acute lymphoblastic leukemia. The overall health care cost burden of a patient is determined by the type of service received, where it was received, who provided it and its duration. This study investigated ancillary, inpatient, outpatient, pharmacy and professional costs in addition to total cost in an attempt to distinguish how the cost of each type of service impacts the total cost to the patient. Acute leukemia patient characteristics of the study population were consistent with those reported nationally.[15] Patient characteristics were consistent between each criterion, with a mean age of either 27 or 28 and a higher percentage of males, as would be expected from the higher rate of leukemia diagnoses in males. Such demographics are similar to national Surveillance, Epidemiology, and End Results (SEER) statistics, which report a higher percentage of men with acute leukemia diagnoses as well as both a younger acute lymphoblastic leukemia population and an older acute myeloid leukemia population.[15]

Our study found certain patient characteristics to be predictive of cost; however, it also revealed that health care costs of rare disease populations may not follow cost patterns for more common disease. Prior research identifies increasing age as a factor associated with higher health care utilization rates and costs.[16] This study found that the younger age of an acute leukemia patient is associated significantly with higher average cost. Bertakis et al. identified a gender difference in the use of health care services, with a higher rate of use in women.[17] However, in this study population, men had higher costs. Billings et al. found higher rates of hospitalization in low-income areas attributed to less timely and effective outpatient care.[18] For certain cost variables in our study the opposite was found, in that inpatient cost was lower in low-income areas.

Other study results were consistent with more typical health care cost patterns. Zweifel et al. reported cost of treatment to be an important driver of total cost,[19] similar to our study's findings. Patients receiving treatment with HCT experienced significantly higher cost when compared to those treated only with chemotherapy. This finding is consistent with the identification of HCT as the procedure with the most rapidly increasing cost between 2004 and 2007.[20] Advances in scientific knowledge have expanded HCT treatment to a variety of hematologic diseases and disorders; however, its high cost makes it vulnerable to cost containment. As expected, patients with higher severity of illness had higher cost associated with an increased need for health care services. In the Andersen model, socioeconomics is considered a factor that may impact how patients use health care services, with higher socioeconomic status supporting higher utilization.[5] Findings of this study support the theory of lower costs associated with lower utilization and lower socioeconomic status. Finally, the direction of study findings were not consistent between the different types of services received and underscore the complexity of understanding the factors that drive the total cost outcome.

Study Limitations

The study's research design was restricted because of the limitations of data available in the WHIO administrative claims database. Data censoring due to death and changes in patient insurance influence the amount of follow-up claims data available, and such causes were not delineated in the database. The study population was defined by a subset of Wisconsin insurance claims and did not include patients who did not pay with insurance or used insurance administered from a different U.S. state. Patient ZIP code was available at the county level only, and its specificity was reduced. Assessment of interactions was outside the scope of the analysis due to the number of potential combinations. Finally, analysis of cost data was complex due to its tendency to be skewed, with long, right tails, multiple zero values and large differences in rates of health services utilization causing a higher proportion of heath care cost to be attributed to a smaller group of patients, and a non-normal distribution of data.

CONCLUSIONS

Health care costs of less common diseases such as acute leukemia may not follow patient characteristic patterns found in more common disease populations. Using Andersen's behavioral model of health care utilization, study variables were identified that represent patient and community factors expected to influence cost. Based on a generalized linear model fitting gamma-distributed data with log-link technique, individual and community factors were found to be significant predictors within each cost criterion and provide opportunities for further investigation of higher costs at the patient, provider and community levels. Assessing the unique influence of each variable on each cost outcome as well as further exploration into types of treatment offered by providers in different socioeconomic locations is advisable.

Patient-Friendly Recap

- Health care costs for patients with leukemia are substantial.
- The authors reviewed statewide data to determine which patient, provider and community factors drive up total cost.
- They found that type of treatment received and disease severity were the biggest contributors to higher cost, but also observed a jump in patients receiving at least some of their treatment from an academic medical center.
- Inpatient and pharmacy costs were lower when providers were located in impoverished areas, raising the possibility of treatment disparities.

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Conflicts of Interest

None.

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