

# Predicting Costs With Diabetes Complications Severity Index in Claims Data

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**T**he increasing prevalence and growing medical expenditures for diabetes mellitus have made it one of the major healthcare issues in the United States.<sup>1,3</sup> One approach to containing diabetes-related medical expenditures is to enroll diabetes patients in disease management programs so that their medical care can be integrated while their quality of medical services is monitored.<sup>4,5</sup> However, due to limited resources, a healthcare plan cannot enroll all patients in such programs. Because a very small proportion of patients consume a relatively large amount of medical resources,<sup>6,7</sup> targeting disease management to these patients may be an efficient use of resources.

The Diabetes Complications Severity Index (DCSI), developed by Young and colleagues,<sup>8</sup> uses diagnosed complications and laboratory results to assess the level of risk of adverse outcomes for diabetes patients, including hospitalizations and mortality. Even though the DCSI score has just been established, it has been quickly adopted by many researchers.<sup>9-13</sup> However, DCSI's utility as a risk measure for individuals with diabetes may be limited. First, laboratory test results were included during the construction of the DCSI, limiting its use if laboratory results are unavailable, as is typical in most administrative data. Second, the performance of the DCSI has not been evaluated for explaining costs—an outcome that is important for healthcare providers and health services researchers. Third, the DCSI was developed using a patient sample from Washington State; its generalizability to other populations with diabetes is untested.

Therefore, we aimed to extend the usefulness of the DCSI without laboratory test results as a predictor of diabetes severity and to consider its possible use in disease management programs. We previously compared the DCSI with laboratory results with the DCSI without laboratory results for predicting hospitalization, and found that the index was similarly predictive with and without laboratory values.<sup>14</sup> In the current study, we addressed 3 hypotheses. First, the DCSI without laboratory results is a good predictor of healthcare costs. Second, the DCSI without laboratory results is a better measure of diabetes severity than counts of complications. Third, the DCSI without laboratory results explains concurrent costs better than future costs.

**Objectives:** To test the usefulness of the Diabetes Complications Severity Index (DCSI) without laboratory test results in predicting healthcare costs, for potential use in disease management programs.

**Study Design:** Retrospective cohort study using up to 2 years of claims data from 7 health insurance plans.

**Methods:** Individuals with diabetes mellitus and continuous enrollment were study subjects. The DCSI (sum of 7 diabetes complications graded by severity as 0, 1, or 2; range 0-13) and count of diabetes complications (sum of 7 diabetes complications without severity grading; range 0-7) were the main independent variables and were generated using only diagnostic codes. We analyzed 5 types of healthcare costs (ie, total costs, inpatient costs, hospital other costs, pharmacy costs, and professional costs) attributable to the DCSI and the complication count with linear regression models, both concurrently and prospectively.

**Results:** The DCSI without laboratory data was a better predictor of costs than was complication count (adjusted  $R^2$  of total costs: 0.095 vs 0.080). The DCSI explained concurrent costs better than future costs (adjusted  $R^2$  of total costs: 0.095 vs 0.019). There were important differences in healthcare utilization among people stratified by DCSI scores: 5-fold and 3-fold differences in concurrent and prospective total costs, respectively, across 4 DCSI groups.

**Conclusions:** The DCSI without laboratory data may be useful for stratifying individuals with diabetes into morbidity groups, which can be used for selection into disease management programs or for matching in observational research.

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## METHODS

### Design

This was a retrospective cohort study using up to 2 years of claims data in which we tested the value

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### Take-Away Points

The Diabetes Complications Severity Index (DCSI) without laboratory test results can be used to explain 5 different types of healthcare costs: total costs, inpatient costs, hospital other costs, pharmacy costs, and professional costs.

- Significant differences in medical utilization existed among people stratified by DCSI scores without laboratory test results.

- The DCSI without laboratory test results may be useful for stratifying individuals with diabetes into morbidity groups as a selection criterion for disease management programs or as a matching factor for research.

of the DCSI for explaining medical utilization and classifying individuals with diabetes without laboratory data.

### Data

We accessed claims data from 7 Blue Cross Blue Shield plans; the detailed information was described previously.<sup>15</sup> The original data, collected from 2002 to 2005, were subsequently updated with additional data on the original individuals through December 2006. The following data were acquired: (1) enrollment files for administrative data; (2) benefits information to determine medical and pharmacy coverage; and (3) inpatient, outpatient, and pharmacy claims records containing *International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM)* diagnosis, Current Procedural Terminology codes, National Drug Codes, costs, and charges (submitted, allowed, and paid).

### Defining the Analytic Cohort

For inclusion in our analytic cohort, we required that the enrollees have diabetes and 12 months of coverage, including pharmacy coverage, in each calendar year over the study period.

We defined individuals as having type 2 diabetes mellitus if they had 1 relevant inpatient code or 2 outpatient ICD-9-CM codes separated by at least 30 days. The relevant codes were 250.xx, 648.0 (diabetes mellitus with pregnancy), 362.0 (diabetic retinopathy), or 266.41 (diabetic cataract). Individuals with only code 250.x3 (type 1 diabetes mellitus) were not included. Additionally, any individual filling a prescription for a medication for treatment of hyperglycemia was included (eAppendix A, available at [www.ajmc.com](http://www.ajmc.com)). Combination medications were also identified. If the prescription was for metformin alone, the individual was also required to have an ICD-9-CM code for diabetes for inclusion in this group. The calendar year of the earliest diagnosis of diabetes was used as the starting point of the observation period.

### Construction of Costs

Costs were obtained from the claims. Total costs were examined as well as several subcategories: inpatient costs, hospital other costs, pharmacy costs, and professional costs. These costs were standardized to adjust for differences in reimburse-

ment between plans and for inflation over time. Professional services refer to services submitted on professional claims, and include things such as visit costs, laboratory costs, and diagnostic imaging.

Inpatient costs were standardized using the Diagnosis-Related Groups (DRGs) and the Centers for Medicare

& Medicaid Services (CMS) national average inpatient cost per DRG. Professional services costs were standardized using the procedure code and the CMS Resource-Based Relative Value Scale unit for the procedure. All other costs were calculated using the total amount paid as submitted on the claim (total amount paid = amount paid by plan + amount paid out of pocket by enrollees including copay, deductible, and coinsurance + amount paid for coordination of benefits). If an inpatient cost or professional services cost could not be standardized due to an invalid DRG or invalid procedure code, respectively, it was standardized using the total amount paid.

### DCSI, DCSI Complication Count, and Covariates

To replicate the DCSI and DCSI complication counts, we used ICD-9-CM codes and the classification method described by Young and colleagues.<sup>8</sup> The DCSI consists of scores (0, 1, or 2) from 7 complication categories: retinopathy, nephropathy, neuropathy, cerebrovascular, cardiovascular, peripheral vascular disease, and metabolic (range 0-13). The DCSI complication count is a count of any complication in the 7 categories (range 0-7). We did not include laboratory results in constructing DCSI and DCSI complication counts. Inclusion of laboratory results would only affect the complication category of nephropathy. Whereas 6 diagnosis codes could contribute 1 to the DCSI score, 3 laboratory results could have the same contribution; in addition, whereas 3 diagnosis codes could contribute 2 to the DCSI score, only 1 laboratory result could make the same contribution.

### Time Frame for Analyses

We performed 2 sets of analyses in this study: concurrent costs and prospective (next-year) costs. The complete enrollment requirements for the concurrent and prospective analyses were 1 year and 2 years, respectively. For both analyses, the information to construct the independent variables came from the calendar year of the qualifying diabetes diagnosis, to match what was done by Young and colleagues.<sup>8</sup> Outcome variables were derived from the calendar year for the concurrent analysis and the subsequent year for the prospective analysis.



## Statistical Methods

We applied a linear regression model for estimating costs because it generates the highest adjusted  $R^2$  under many circumstances.<sup>16</sup>

We reported and compared the incremental increase of costs and measures of overall model fit, the adjusted  $R^2$ . The adjusted  $R^2$  for costs was obtained from split-half analysis to control for overfitting. We tested inclusion of the main independent variables, DCSI and DCSI complication count, categorically (0, 1, 2, 3, 4, 5+) and linearly. In categorical analysis, the incremental increase of costs was derived by comparing samples in a given category with those in category 0; in linear analysis, it was the incremental increase of costs associated with 1 unit of increase in either the DCSI or DCSI complication count.

## Use of DCSIs for Disease Management Programs

We divided the study sample into 4 groups by DCSI: 0, 1, 2, and 3+, and compared characteristics by DCSI groups.

## Review

The data were de-identified in accordance with the Health Insurance Portability and Accountability Acts (HIPAA) definition of a limited data set. The Johns Hopkins University Office of Research Subjects deemed the study to be exempt from federal regulations because the research activities were considered to be of minimal risk to subjects, as the subjects were not identifiable.

## RESULTS

### Characteristics of the Study Samples

There were 575,327 and 372,982 individuals in the concurrent and prospective analyses, respectively (Table 1). In both cohorts, the mean age was 58 years and 51% were male. The mean DCSI was 0.46 and DCSI complication count was 0.33. The mean annual total, professional, and other hospital costs were similar in both groups: \$11,500, \$2100, and \$2300, respectively. The inpatient costs were higher in the individuals in the concurrent analysis, while the pharmacy costs were higher in individuals in the prospective analysis.

**Table 1.** Characteristics of Study Samples

Characteristic	Type of Analysis <sup>a</sup>	
	Concurrent (n = 575,327)	Prospective (n = 372,982)
Age $\pm$ SD, y <sup>b</sup>	57.5 $\pm$ 13.5	57.9 $\pm$ 13.0
Male <sup>b</sup>	51.47%	51.13%
<b>DCSI score (0-13)</b>		
Mean $\pm$ SD	0.46 $\pm$ 0.97	0.46 $\pm$ 0.96
0	74.86%	74.41%
1	12.67%	13.10%
2	7.92%	8.00%
3	2.42%	2.43%
4	1.27%	1.24%
5+	0.86%	0.81%
<b>DCSI complication count (0-7)</b>		
Mean $\pm$ SD	0.33 $\pm$ 0.66	0.34 $\pm$ 0.66
0	74.86%	74.41%
1	18.99%	19.42%
2	4.60%	4.65%
3	1.21%	1.18%
4	0.29%	0.28%
5+	0.06%	0.05%
<b>Hospitalizations</b>		
Mean $\pm$ SD	0.28 $\pm$ 0.79	0.24 $\pm$ 0.71
0	81.68%	83.90%
1	13.06%	11.43%
2	3.29%	2.96%
3	1.06%	0.94%
4	0.43%	0.37%
5+	0.48%	0.39%
<b>Costs, mean <math>\pm</math> SD</b>		
Total	\$11,900 $\pm$ \$26,600	\$11,500 $\pm$ \$29,800
Inpatient	\$5300 $\pm$ \$18,600	\$4400 $\pm$ \$15,400
Professional	\$2100 $\pm$ \$5500	\$2100 $\pm$ \$5400
Hospital other	\$2400 $\pm$ \$8200	\$2300 $\pm$ \$8600
Pharmacy	\$2100 $\pm$ \$10,600	\$2600 $\pm$ \$20,000

DCSI indicates Diabetes Complications Severity Index.

<sup>a</sup>Concurrent: both outcomes and predictors came from the same year. Prospective: predictors came from the base year while outcomes came from the subsequent year.

<sup>b</sup>2.5% and 3% had missing data on age and sex in the concurrent cohort; 0.6% had missing data on age and sex in the prospective cohort; 0.2% had missing data on age and sex in the combined cohort.

### DCSI Versus DCSI Complication Count

In explaining 5 categories of concurrent and prospective costs, the incremental increases of costs associated with each unit increase in the DCSI were lower than those in the



■ **Table 2.** Incremental Increase of Total Costs by Main Predictors, Types of Costs, and Study Sample<sup>a</sup>

DCSI Score	Incremental Cost Increase, \$	DCSI Complication Count	Incremental Cost Increase, \$
<b>Categorical</b>			
Concurrent (n = 575,327)			
0 (reference)	—	—	—
1	5100 <sup>b</sup> (4903, 5297)	1	8916 (8748, 9084)
2	15,737 (15,495, 15,980)	2	23,786 (23,471, 24,101)
3	25,585 (25,161, 26,009)	3	42,500 (41,899, 43,101)
4	38,735 (38,155, 39,316)	4	62,262 (61,036, 63,488)
5+	60,663 (59,961, 61,365)	5+	82,126 (79,431, 84,821)
Prospective (n = 372,982)			
0 (reference)	—	—	—
1	3651 (3368, 3933)	1	5667 (5426, 5907)
2	9588 (9238, 9938)	2	14,204 (13,753, 14,655)
3	15,161 (14,548, 15,775)	3	24,223 (23,348, 25,098)
4	22,657 (21,805, 23,509)	4	34,112 (32,314, 35,910)
5+	33,435 (32,386, 34,484)	5+	51,098 (46,860, 55,336)
<b>Linear</b>			
Concurrent (n = 575,327)			
One-unit increase	8979 (8912, 9046)	One-unit increase	12,028 (11,928, 12,128)
Prospective (n = 372,982)			
One-unit increase	5236 (5138, 5334)	One-unit increase	7101 (6957, 7245)

DCSI indicates Diabetes Complications Severity Index.

<sup>a</sup>Observations with missing age or sex were not in the adjusted models.

<sup>b</sup>Compared with people who had a DCSI equal to 0, those who had a DCSI equal to 1 had total costs that were on average \$5100 higher, after controlling for other variables.

DCSI complication count, both categorically and linearly (Table 2 and eAppendix B, available at [www.ajmc.com](http://www.ajmc.com)). For total costs, for example, categorically the differences in the incremental increases between 2 models ranged from \$4000 to \$22,000 in the concurrent analyses and from \$2000 to \$20,000 in the prospective analyses; linearly, the difference was \$3000 and \$2000 in the concurrent and prospective analyses, respectively. For overall model fit, the DCSI models generally had higher or similar adjusted R<sup>2</sup> values compared with the DCSI complication count models (Table 3). For example, the unadjusted concurrent R<sup>2</sup> of total cost of DCSI was 0.095 while that of DCSI complication count was 0.08.

### Concurrent Versus Prospective Analyses

The incremental increases of total, inpatient, and professional costs attributable to the DCSI score were consistently higher in the models using concurrent data compared with those models predicting future costs (Table 2 and eAppendix 2). For total costs, for example, the difference between 2 models ranged from \$1500 to \$27,000 categorically, and

\$3700 linearly. The incremental increases in pharmacy costs, however, were predicted to be higher in the prospective models than in the concurrent models. The adjusted R<sup>2</sup> was always higher concurrently than prospectively (Table 3); the largest difference in the R<sup>2</sup> values was in inpatient costs (0.02) and total costs (0.015); the smallest was in pharmacy costs (0.001).

### Potential Use of DCSI for Disease Management Programs

The mean age increased from 56 to 65 years across DCSI categories; about 50% were male in DCSI groups 0 and 1; the proportion who were

male approached 60% in DCSI groups 2 and 3+ (Table 4). Medical care costs increased across DCSI categories, both concurrently and prospectively. Such increases were the largest in the inpatient and total costs (7-fold and 5-fold differences concurrently, and 4-fold and 3-fold differences prospectively), and the smallest in the pharmacy costs (about 2-fold both concurrently and prospectively). The inpatient and total costs increased from \$3200 and \$8400 in DCSI group 0 to \$25,900 and \$44,300 in DCSI group 3+ in the concurrent analyses, and from \$3400 and \$9300 to \$13,600 and \$29,900 in the prospective analyses.

## DISCUSSION

We found that the DCSI without laboratory test results can be used to explain 5 different types of healthcare costs and that the DCSI without laboratory data was a better predictor of costs than the DCSI complication count. The DCSI without laboratory data predicted costs better concurrently than prospectively.



## Validation of DCSI

■ **Table 3.** Adjusted  $R^2$  of Costs by Main Predictors, Types of Cost, and Study Sample

Type of Analysis	Total Costs	Inpatient Costs	Professional Costs	Hospital Other Costs	Pharmacy Costs
<b>Concurrent</b>					
DCSI					
Categorical	0.095	0.091	0.041	0.045	0.001
Linear	0.094	0.087	0.041	0.045	0.001
DCSI complication count					
Categorical	0.081	0.073	0.040	0.037	0.001
Linear	0.078	0.069	0.040	0.036	0.001
<b>Prospective</b>					
DCSI					
Categorical	0.019	0.025	0.018	0.026	0.000
Linear	0.019	0.025	0.018	0.025	0.000
DCSI complication count					
Categorical	0.017	0.022	0.017	0.020	0.000
Linear	0.016	0.022	0.018	0.018	0.000

DCSI indicates Diabetes Complications Severity Index.

■ **Table 4.** Characteristics of Study Samples by DCSI Group

Type of Analysis	DCSI Group			
	0	1	2	3+
<b>Concurrent</b>				
No.	430,662	72,903	45,568	26,194
Age $\pm$ SD, y <sup>a</sup>	56.2 $\pm$ 13.5	59.8 $\pm$ 12.9	62.3 $\pm$ 12.7	65.3 $\pm$ 12.3
Male <sup>a</sup>	50.84%	49.34%	57.16%	58.35%
Costs, mean $\pm$ SD, \$				
Total	8400 $\pm$ 20,700	13,500 $\pm$ 22,100	24,100 $\pm$ 36,600	44,300 $\pm$ 57,600
Inpatient	3200 $\pm$ 13,100	5500 $\pm$ 16,700	12,900 $\pm$ 28,200	25,900 $\pm$ 45,400
Professional	1600 $\pm$ 4000	2900 $\pm$ 6000	3600 $\pm$ 7600	6300 $\pm$ 13,100
Hospital other	1700 $\pm$ 5300	2600 $\pm$ 6600	4800 $\pm$ 14,300	8700 $\pm$ 22,100
Pharmacy	1900 $\pm$ 12,100	2500 $\pm$ 3500	2800 $\pm$ 4100	3500 $\pm$ 4600
<b>Prospective</b>				
No.	277,553	48,856	29,824	16,749
Age $\pm$ SD, y <sup>a</sup>	56.5 $\pm$ 12.9	60.2 $\pm$ 12.4	62.6 $\pm$ 12.3	65.4 $\pm$ 11.8
Male <sup>a</sup>	50.58%	48.68%	56.45%	58.14%
Costs, mean $\pm$ SD, \$				
Total	9300 $\pm$ 28,900	13,000 $\pm$ 22,400	18,900 $\pm$ 33,400	29,900 $\pm$ 44,200
Inpatient	3400 $\pm$ 12,700	5100 $\pm$ 16,700	7900 $\pm$ 21,600	13,600 $\pm$ 29,100
Professional	1800 $\pm$ 4800	2700 $\pm$ 5900	3200 $\pm$ 7200	4600 $\pm$ 8300
Hospital other	1800 $\pm$ 5500	2300 $\pm$ 6200	4300 $\pm$ 17,100	7500 $\pm$ 21,800
Pharmacy	2400 $\pm$ 23,000	3000 $\pm$ 3800	3400 $\pm$ 4500	4200 $\pm$ 5100

DCSI indicates Diabetes Complications Severity Index; SD, standard deviation.

<sup>a</sup>2.5% and 3% had missing data on age and sex in the concurrent cohort; 0.6% had missing data on age and sex in the prospective cohort.



Extending the work of Young and colleagues,<sup>8</sup> we showed here that the DCSI without laboratory data could explain various types of healthcare costs. This greatly expands the applicability of DCSI because claims data are often more accessible than health record data with laboratory results. Claims data have been used for the general adjustment for differences in morbidity burden<sup>16,17</sup> and the identification of high-risk cases<sup>18-20</sup> both domestically and internationally, such as the Adjusted Clinical Groups system<sup>21</sup> or Diagnostic Cost Group.<sup>22</sup> However, these risk measures were developed for the general population and have not been tailored to a given disease group. Given various types of diseases, the general approach may not be detailed enough and it may be necessary to develop disease-specific measures to complement what the general approach can achieve.

Given the existence of many distinct characteristics in demographics, outcomes, and model performances by DCSI groups, the DCSI might serve as a classification scheme for health insurance plans to identify the highest risk group of patients with diabetes. In our study, patients with a DCSI score of 3 or higher (4.6% of the total sample) consumed about 17% of the total medical resources utilized by all study samples. Because of the limited resources available to health insurance plans to enroll individuals with diabetes in disease management, the largest cost benefits might come from enrolling people with the highest expected costs in the program; this can be done through the application of the DCSI.

The much better performance of the DCSI concurrently rather than prospectively can be expected given that both outcomes and independent variables were derived from the same period. Concurrent analyses are typically used for the purpose of provider profiling or outlier identification since patients with similar morbidity, known from claims information, should have similar utilization of medical resources. The DCSI might be applied in the same manner to help healthcare plans identify clinicians whose patient care costs are higher or lower than would be expected given the morbidity of his/her patient panel.

Our study has several potential limitations. If out-of-network services were used, the health insurance plan would not acquire diagnosis information since submission for reimbursement was not necessary. In addition, even though our study sample came from 7 health insurance plans across different regions in the United States, how representative this study sample is of the whole diabetes population needs to be explored further; thus, readers have to be cautious in generalizing the results of our study to other populations with patients with diabetes. The majority of the study sample (more than 80%) were assigned to group 0 on both the DCSI score and the complication count. This skewed distribution might impact the per-

formance of the DCSI adversely, given the lack of variability. Therefore, future research might be necessary to examine how the DCSI performs prospectively in a population that includes patients with more morbidity, and we might be able to identify the best situation where the DCSI can be applied. Future research might also further explore the atypical patterns with pharmacy costs. This study showed that the DCSI had the least success in explaining pharmacy costs. This could suggest that individuals with many complications of diabetes fill fewer of their prescriptions. Given that pharmacy data are part of routinely collected claims data, it might be necessary to incorporate pharmacy data into the construction of the DCSI or complement the DCSI with pharmacy-based severity measures for research involving pharmacy utilization as a main interest.

## CONCLUSIONS

The DCSI without laboratory data is a good measure of diabetes severity, given its explanatory ability regarding 5 different types of healthcare costs both concurrently and prospectively. However, given the differences in its performance (much better concurrently than prospectively; much worse with pharmacy costs than other types of costs), readers have to be attentive when using this index. The best application of the DCSI may be for stratifying individuals with diabetes into different morbidity groups as a selection criterion for disease management programs or as a matching factor for research.

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