



Comparison of the Performance of a Newly Developed Risk Adjustment Tool, Diagnostic Items, with the Charlson Comorbidity Method in Predicting Hospital Mortality

J. KIM^{1,2}, C. Lee³

1 Department of Preventive Medicine, University of Ulsan College of Medicine, Seoul, Republic of Korea
2 Institute of Health Policy and Management, Seoul National University Medical Research Center, Seoul, Republic of Korea
3 Boston University, Boston, United States

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INTRODUCTION AND AIM

This study aims to assess the performance of a newly developed diagnostic classification system for costs, Diagnostic Items (DXIs) as a risk adjustment method in predicting mortalities. We compared the model performance between DXIs and widely used Charlson comorbidity method, using admission claims data.

METHOD

Our study used National Health Insurance Service-National Sample Cohort in 2013.¹ We split the dataset into 90% and 10% for estimation and validation, respectively. We conducted a logistic regression analysis to estimate mortalities, including sex, age group (0–4 years, 5–9 years, 10–14 years, 15–19 years, 20–24 years, 25–29 years, 30–34 years, 35–39 years, 40–44 years, 45–49 years, 50–54 years, 55–59 years, 60–64 years, 65 years and over), socioeconomic status (low socioeconomic status vs. the others), and comorbidities. The low socioeconomic status includes Medicaid and the first quintile of income. Then, we compared the performance of models depending on the risk adjustment methods for comorbidities (DXIs or Charlson comorbidity method).

Full DXIs consist of three types: main effect DXIs (diseases), modifiers (such as laterality or timing), and scaled variables (such as gestational age) (Fig 1)² We used the main effect DXIs focusing on clinical dimensions (N=2,435). Regarding the Charlson comorbidity method, we used categorical variables (17 groups)³, as seen in DXIs, instead of the Charlson Comorbidity Index (CCI). Additionally, we also adopted a stepwise variable selection. The model performance was evaluated using a Area Under the Curve (AUC). This study was exempted from the Institutional Review Board because we used deidentified secondary dataset (2023-0034).

Fig 1. Structure of DXIs

DXIs			
Main effects	Modifiers		Scales
AMI STEMI	- Left - Right	- Acute - Subsequent	
Preexisting hypertension			- First trimester - Second trimester - Third trimester

RESULTS

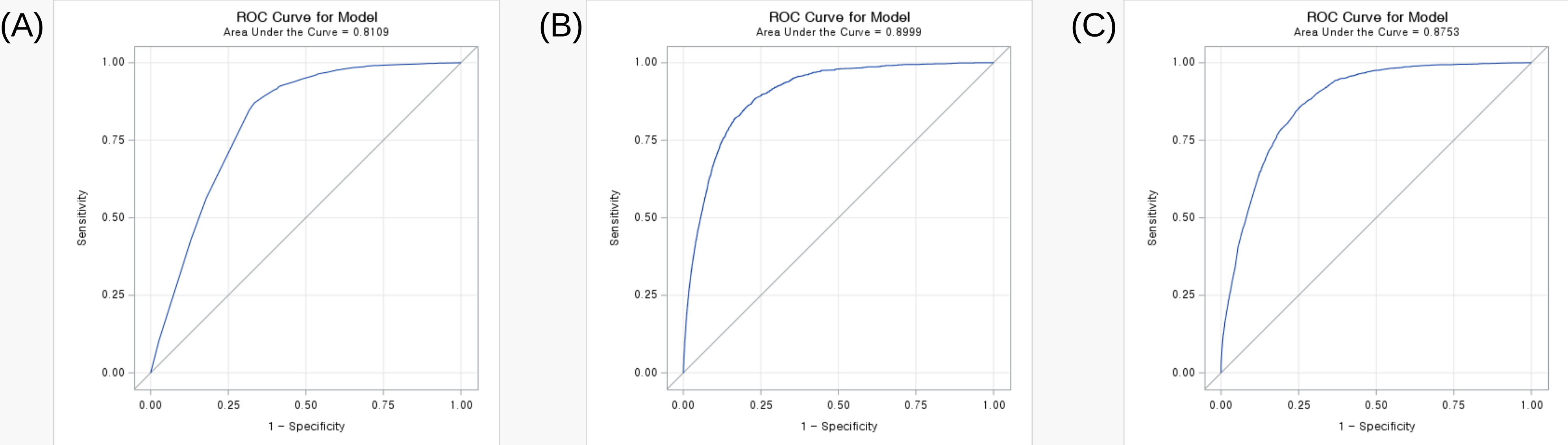
The data (N=124,068) were divided into estimation (N=111,673) and validation (N=12,395) datasets. About half of the sample was female in both the estimation (55.5%) and validation datasets (55.2%) (Table 1). The distribution of age groups was similar between datasets. Less than 20% were classified as low socioeconomic status.

Table 1. Sociodemographic of study population, n (%)

Variables		Estimation dataset (N=111,673)	Validation dataset (N=12,395)
Female		62,030 (55.5)	6,839 (55.2)
Age group	0-4 years	1,674 (1.5)	188 (1.5)
	5-9 years	6,317 (5.7)	697 (5.6)
	10-14 years	2,786 (2.5)	282 (2.3)
	15-19 years	2,119 (1.9)	227 (1.8)
	20-24 years	3,163 (2.8)	354 (2.9)
	25-29 years	3,683 (3.3)	421 (3.4)
	30-34 years	5,059 (4.5)	551 (4.4)
	35-39 years	8,851 (7.9)	961 (7.8)
	40-44 years	6,679 (6.0)	728 (5.9)
	45-49 years	6,966 (6.2)	762 (6.1)
	50-54 years	7,893 (7.1)	880 (7.1)
	55-59 years	10,044 (9.0)	1,112 (9.0)
	60-64 years	9,203 (8.2)	1,068 (8.6)
	65 years and over	37,236 (33.3)	4,164 (33.6)
Low socioeconomic status		21,590 (19.3)	2,466 (19.9)

The AUC of the basic model (only sociodemographics) was 0.81 (95% CI 0.81-0.82). Although the models adding comorbidities improved performance, the new DXI (0.90, 95% CI 0.90-0.90) did not show superiority compared to the Charlson's method (0.88, 95% CI 0.87-0.88) (Fig 2, Table 2). The stepwise variable selection did not improve model performance in all models. The validation dataset's results were similar overall to those from the estimation dataset. Although the Charlson's method showed good performance, 17 categories might not be enough to explain complicated comorbidity states. On the other hand, too many clinical states of DXIs (over 2,000 main effects) can also hinder model performance improvement.

Fig 2. ROC curves of models (estimation dataset) (A) M1, (B) M2, (C) M3



ROC, Receiver Operating Characteristic.

Table 2. Performance of models

Model			Estimation dataset		Validation dataset	
			AUC	95% CI	AUC	95% CI
M1	OLS	Sociodemographics only	0.81	(0.81, 0.82)	0.80	(0.79, 0.82)
M2		Sociodemographics, Charlson's method	0.90	(0.90, 0.90)	0.91	(0.89, 0.92)
M3		Sociodemographics, DXIs	0.88	(0.87, 0.88)	0.89	(0.88, 0.90)
M4	Stepwise OLS	Sociodemographics only	0.81	(0.81, 0.82)	0.80	(0.78, 0.81)
M5		Sociodemographics, Charlson's method	0.90	(0.90, 0.90)	0.90	(0.89, 0.92)
M6		Sociodemographics, DXIs	0.83	(0.83, 0.84)	0.79	(0.78, 0.81)

AUC, Area Under the Curve; CI, Confidence Interval; OLS, Ordinary Least Squares; DXIs, Diagnostic Items.

CONCLUSIONS

DXIs, the new diagnostic classification system developed to estimate cost, did not show superiority over the Charlson's method in mortality estimation. Considering that the main effect of the DXIs is initial categories, our results can imply that the DXIs should be refined by clustering or adopting a hierarchical structure of meaningful clinical states.

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CONTACT INFORMATION

Juyoung Kim, RN, MSc, PhD
juyoungkim0716@gmail.com