



The HOMR-Now! Model Accurately Predicts 1-Year Death Risk for Hospitalized Patients on Admission

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ABSTRACT

BACKGROUND: The Hospital-patient One-year Mortality Risk (HOMR) score is an externally validated index using health administrative data to accurately predict the risk of death within 1 year of admission to the hospital. This study derived and internally validated a HOMR modification using data that are available when the patient is admitted to the hospital.

METHODS: From all adult hospitalizations at our tertiary-care teaching hospital between 2004 and 2015, we randomly selected one per patient. We added to all HOMR variables that could be determined from our hospital's data systems on admission other factors that might prognosticate. Vital statistics registries determined vital status at 1 year from admission.

RESULTS: Of 2,06,396 patients, 32,112 (15.6%) died within 1 year of admission to the hospital. The HOMR-now! model included patient (sex, comorbidities, living and cancer clinic status, and 1-year death risk from population-based life tables) and hospitalization factors (admission year, urgency, service and laboratory-based acuity score). The model explained that more than half of the total variability (Regenkirke's R^2 value of 0.53) was very discriminative (C-statistic 0.92), and accurately predicted death risk (calibration slope 0.98).

CONCLUSION: One-year risk of death can be accurately predicted using routinely collected data available when patients are admitted to the hospital.

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KEYWORDS: Administrative data; Calibration; Discrimination; Hospitalization; Mortality; Multivariate logistic regression; Risk index; Risk model; Risk score; Survival

Funding: This study was supported by the Institute for Clinical Evaluative Sciences (ICES), which is funded by an annual grant from the Ontario Ministry of Health and Long-Term Care (MOHLTC). The opinions, results, and conclusions reported in this paper are those of the authors and are independent from the funding sources. No endorsement by ICES or the Ontario MOHLTC is intended or should be inferred. Parts of this material are based on data and information compiled and provided by Canadian Institute for Health Information (CIHI). However, the analyses, conclusions, opinions, and statements expressed herein are those of the author, and not necessarily those of CIHI.

Conflict of Interest: Neither author has any conflicts of interest to declare.

Authorship: Both authors had access to the data and played a role in writing the manuscript.

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Patient death risk can influence many clinical decisions in medical care.¹ Several validated multivariable indexes have been created to predict survival in patients.¹ The accuracy and utility of these indexes range broadly, but all require the acquisition and input of a varying number of patient-specific information. We recently created and externally validated the Hospitalized-patient One-year Mortality Risk (HOMR) model, which accurately estimates 1-year death risk in patients admitted to the hospital using health administrative data.^{2,3}

However, the HOMR score cannot be used in “real time” to help with clinical decision-making during the patient's hospitalization because the primary dataset used to create the HOMR (the hospitalization discharge abstract) is created

only *after* the patient's discharge. This makes it impossible to calculate the HOMR when the patient gets admitted to the hospital. In this study, we derived and internally validated a HOMR modification that is calculable on patient admission using data commonly available within hospital data warehouses.

METHODS

The study took place at a 1000-bed tertiary-care teaching hospital and was approved by our local research ethics board. We used our hospital's admission registry to identify all adults admitted to a nonpsychiatric service between January 1, 2004 and December 31, 2014.

The HOMR score contains 10 variables from population-based health administrative data (Supplementary Tables 1-3, Appendix, available online). Immediately when patients are admitted, we could determine values for 5 of these variables with our hospital's data systems (patient age and sex; admission service; admission urgency; living status). We used proxy measures for 3 variables (the number of emergency department visits and admissions by ambulance in the previous year could be determined for our hospital only, and we calculated the Charlson comorbidity score⁴ [using diagnostic codes from Quan et al⁵ and disease-specific weights from Schneeweiss et al⁶] using diagnostic codes for admissions at our hospital only during the previous 3 years). Two HOMR score variables (home oxygen status and admission diagnostic risk score) could not be determined.

To address these potential data deficiencies, we added 2 new covariates to our model. First, we used population life tables for Ontario to determine each person's age-sex-specific 1-year death risk. Annual life tables were available for 2006 to 2010. Second, we used laboratory test results measured from 48 hours prior to admission to 6 hours after admission to calculate the Laboratory-based Acute Physiological Score (LAPS),⁷ which combines information from 14 lab tests into a single weighted score that predicted death in the hospital.

These data were encrypted and linked anonymously to population-based databases to determine whether patients died within 1 year of admission to the hospital. We first used fractional polynomial methods to determine the first-degree transformations for continuous covariates (and their interactions) that maximized data fit (this let us determine the best fit for noncategorical variables).^{8,9} We then used bootstrapping methods (with 500 bootstrap samples) to identify variables independently associated with 1-year death (this method is very good at excluding variables with spurious associations with the outcome to create

models with greater generalizability).¹⁰ Variables with regression coefficients whose nonparametric 95th percentile credible interval excluded 0 were kept in the final model.¹¹ As suggested by Steyerberg et al,¹² the final model was assessed by measuring overall fit (Regenkirke's R^2), model discrimination (C-statistic), and model calibration (calibration slope). All fit assessments were optimism-corrected using bootstrapping techniques.¹¹

RESULTS

There were 364,858 adult admissions to nonpsychiatric services during the study period for people with a valid health card number. Of these admissions, 158,462 (43.4%) were randomly excluded because the patient already had another admission in the analytical dataset.

This left 206,396 patients in our study cohort (Table 1), with 32,112 patients (15.6%) dying within 1 year of hospital admission. People who died were notably older and more likely to be male, have a life-table death risk exceeding 5%, have a Charlson score above 0, be living in a nursing home or chronic hospital, and have recently visited our cancer clinic or emergency department.

The HOMR-now! model contained 10 variables and 1 interaction (Supplementary Table 4, Appendix, available online). Notably, influential patient factors included an increased number of important comorbidities, living in a nursing home prior to admission, and having visited the cancer clinic in the previous 6 months (Table 2). After adjustment, male sex was associated with a *decreased* death risk. Influential hospitalization factors included urgent admissions by ambulance, being admitted to particular services (such as Neurosurgery, Thoracic Surgery, Trauma, and Hematology-Oncology). Increased LAPS scores were also associated with an increased death risk. Life-table mortality estimates were very strongly associated with 1-year death risk but interacted significantly with admission status (Figure 1): life-table death risk estimates *exceeded* those predicted by the HOMR-now! model in patients admitted electively, but were lower in patients admitted through the emergency department with no ambulance. Model-predicted death risk increased in a nonlinear fashion with a greater number of emergency department visits in the previous year (Figure 2).

The HOMR-now! model explained a large amount of events (optimism-corrected Regenkirke's R^2 value of 0.53) and was highly discriminative (optimism-corrected C-statistic of 0.92). The median expected 1-year death risk from the HOMR-now! model was 4.2% (interquartile range 0.9%-19.2%). There were 42,903 (20.8%) and 22,118 (10.7%) patients who had an expected risk exceeding 25% and 50%, respectively. Observed and expected 1-year death

CLINICAL SIGNIFICANCE

- The HOMR-now! model modified a previously derived and validated prognostic index so that our hospital information system could output 1-year life expectancies when patients are admitted to the hospital.
- The HOMR-now! model was highly discriminative (C-statistic 0.92) and well calibrated (calibration slope 0.98).

Table 1 Study Cohort by Death Status

Variable	Value	Death Status		Overall
		No N = 174,284 (84.4%)	Yes N = 32,112 (15.6%)	N = 206,396
Patient factors				
Mean age at admission (SD)		50.9 ± 20.4	73.0 ± 14.3	54.3 ± 21.2
Male		66,894 (38.4%)	16,578 (51.6%)	83,472 (40.4%)
Expected annual risk of death*	<5%	158,767 (91.1%)	21,208 (66.0%)	179,975 (87.2%)
	5%-<10%	10,491 (6.0%)	6241 (19.4%)	16,732 (8.1%)
	10%-<25%	4856 (2.8%)	4377 (13.6%)	9233 (4.5%)
	25%-<50%	170 (0.1%)	286 (0.9%)	456 (0.2%)
Charlson score†	0	112,952 (64.8%)	3825 (11.9%)	116,777 (56.6%)
	1	27,316 (15.7%)	4643 (14.5%)	31,959 (15.5%)
	2-3	23,534 (13.5%)	9007 (28.0%)	32,541 (15.8%)
	4-5	5808 (3.3%)	3625 (11.3%)	9433 (4.6%)
	6+	4674 (2.7%)	11,012 (34.3%)	15,686 (7.6%)
Living status	Home	153,827 (88.3%)	24,667 (76.8%)	178,494 (86.5%)
	Rehab	7 (0.0%)	6 (0.0%)	13 (0.0%)
	Nursing home	2365 (1.4%)	2618 (8.2%)	4983 (2.4%)
	Chronic hospital	18,085 (10.4%)	4821 (15.0%)	22,906 (11.1%)
Visit to cancer clinic‡	TOH ED visits§	5404 (3.1%)	6886 (21.4%)	12 290 (6.0%)
	0	128,221 (73.6%)	18,108 (56.4%)	146,329 (70.9%)
	1	27,357 (15.7%)	6840 (21.3%)	34,197 (16.6%)
	2-3	14,078 (8.1%)	4991 (15.5%)	19,069 (9.2%)
TOH admissions by ambulance§	4+	4628 (2.7%)	2173 (6.8%)	6801 (3.3%)
	0	167,468 (96.1%)	27,957 (87.1%)	195,425 (94.7%)
	1	5703 (3.3%)	3169 (9.9%)	8872 (4.3%)
	2-3	1018 (0.6%)	874 (2.7%)	1892 (0.9%)
	4+	95 (0.1%)	112 (0.3%)	207 (0.1%)
Hospitalization factors				
Admission urgency	Elective	59,755 (34.3%)	1847 (5.8%)	61,602 (29.8%)
	ED, no ambulance	64,834 (37.2%)	12,033 (37.5%)	76,867 (37.2%)
	ED, ambulance	49,695 (28.5%)	18,232 (56.8%)	67,927 (32.9%)
Admission service	Medicine	26,008 (14.9%)	10,464 (32.6%)	36,472 (17.7%)
	Cardiology	26,294 (15.1%)	2869 (8.9%)	29,163 (14.1%)
	GI/Nephro/Neuro	7050 (4.0%)	1604 (5.0%)	8654 (4.2%)
	General surgery	16,799 (9.6%)	1873 (5.8%)	18,672 (9.0%)
	Cardiovascular surgery	6228 (3.6%)	1008 (3.1%)	7236 (3.5%)
	Neurosurgery	5911 (3.4%)	1382 (4.3%)	7293 (3.5%)
	Ortho/plastics	18,664 (10.7%)	1724 (5.4%)	20,388 (9.9%)
	Thoracic surgery	1632 (0.9%)	582 (1.8%)	2214 (1.1%)
	Trauma	4729 (2.7%)	2603 (8.1%)	7332 (3.6%)
	Urology	4457 (2.6%)	487 (1.5%)	4944 (2.4%)
	Obstetrics	46,594 (26.7%)	14 (0.0%)	46,608 (22.6%)
Gynecology	6280 (3.6%)	572 (1.8%)	6852 (3.3%)	
Heme-oncology	3638 (2.1%)	6930 (21.6%)	10,568 (5.1%)	
Patient admitted directly to ICU		8186 (4.7%)	2112 (6.6%)	10,298 (5.0%)
Current admission is a 30-day urgent readmission		8404 (4.5%)	7613 (4.4%)	3116 (9.7%)
Median LAPS score (IQR)		6 (0-27)	41 (21-62)	13 (0-34)

ED = emergency department; GI = gastrointestinal; ICU = intensive care unit; IQR = interquartile range; LAPS = Laboratory-based Acute Physiological Score; TOH = The Ottawa Hospital.

*From population life tables.

†Using data from previous admissions.

‡In previous 6 months.

§In previous year.

||Admitted urgently (not electively).

Table 2 Association of Categorical and Untransformed Continuous Patient and Admission Factors with 1-Year Death Risk

Variable	Parameter Estimate	Adjusted Odds Ratio	95% Credible Interval
Patient factors			
Patient is male	-0.08	0.92	0.89-0.96
Charlson score increased by 1	0.49	1.63	1.60-1.65
Living status			
Home	Ref	1	—
Rehab	0.72	2.06	0.53-8.05
Nursing home	0.57	1.76	1.63-1.92
Chronic hospital	0.15	1.16	1.11-1.22
Seen in cancer clinic in last half year	0.40	1.49	1.39-1.60
Hospitalization factors			
Admission year			
Before 2006	0.35	1.42	1.31-1.52
2006-2010	Ref	1	—
Each year beyond 2010	-0.11	0.893	0.87-0.90
Admission urgency			
Elective	Ref	1	—
ED, no ambulance*	—	—	—
ED, with ambulance	0.42	1.53	1.42-1.66
Admission service			
Medicine	Ref	1	—
Cardiology	-0.82	0.44	0.41-0.47
GI/Nephro/Neuro	-0.30	0.74	0.70-0.80
General surgery	-0.43	0.65	0.61-0.69
Cardiovascular surgery	-0.36	0.70	0.65-0.76
Neurosurgery	0.66	1.94	1.79-2.09
Orthopedics/Plastics	-0.35	0.71	0.66-0.75
Thoracic surgery	0.70	2.00	1.79-2.26
Trauma	0.73	2.07	1.91-2.23
Urology	-0.45	0.64	0.57-0.72
Obstetrics	-3.10	0.05	0.02-0.07
Gynecology	0.16	1.18	1.05-1.32
Heme-Oncology	1.20	3.31	3.07-3.53
LAPS increased by 10	0.19	1.21	1.19-1.21

This table displays all variables from the Hospital-patient One-year Mortality Risk (HOMR)-now! model (Supplementary Table 4, Appendix, available online) that were either categorical or nontransformed continuous variables that did not interact with other covariates. The parameter estimate for each variable was determined using 500 bootstrap samples.¹² The adjusted odds ratio and 95% credible interval (the range within the true estimate is expected to be found in 95% of all samples) is also presented.

ED = emergency department; GI = gastrointestinal; LAPS = Laboratory-based Acute Physiological Score.⁷

*This variable interacted significantly with life-table death risk; see Figure 1 to examine its association with 1-year death.

risks were very similar (Figure 2), with observed risks slightly exceeding expected risks when the latter ranged between 10% and 50%. The optimism-corrected calibration slope was 0.98, indicating a very strong association between observed and expected death risks.

DISCUSSION

The HOMR-now! model used data immediately available when patients are admitted to the hospital to accurately predict the risk that patients would die within the next year. This could allow physicians to integrate multivariable-based prognostications into their real-time hospital clinical decision-making.

The HOMR-now! model compares favorably with previous created prognostic indexes. Compared with other

indexes for hospitalized patients summarized in Yourman et al's systematic review,¹ the HOMR-now! C-statistic of 0.92 was notably more discriminative than previously published indexes (whose C-statistics ranged from 0.66 to 0.83). Most importantly, the HOMR-now! hospital information systems can be programmed to automatically calculate HOMR-now! when patients are admitted to the hospital. This advantage is important because it should significantly increase the likelihood that physicians use patient-specific prognostication in their decision-making. However, in contrast to other (especially condition-specific¹³) indexes, the HOMR-now! model is notably devoid of any diagnostic information or factors that are commonly accepted by physicians to be of prognostic importance. The lack of such data might limit its face validity to practicing clinicians.

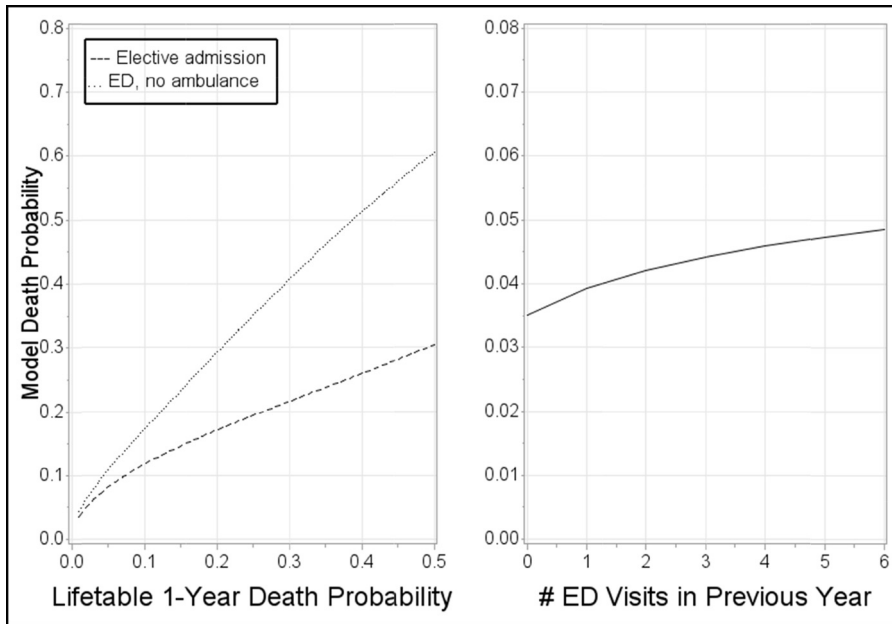


Figure 1 Influence of admission urgency, number of previous emergency visits and life-table annual death risk on expected 1-year death probability from the Hospital-patient One-year Mortality Risk (HOMR)-now! model. These figures display the influence of all continuous variables that were transformed or interacted significantly with other covariates in the HOMR-now! model (Supplementary Table 4, Appendix, available online). These figures plot the 1-year death risk from the model (vertical axis) against the life-table 1-year death probability (left plot) and the number of emergency department (ED) visits in the previous year. The risks presented in both of these figures are for female patients with a Charlson score of 0 and no cancer clinic visits in the previous 6 months who were admitted to a medicine service between 2006 and 2010 with a laboratory abnormality physiological score of 14. In the left plot, patients had no ED visits in the previous year. In the right plot, patients were admitted electively and had a life-table 1-year death probability of 1%.

Several findings from our study are notable. First, our need to limit our model to variables available when patients were admitted, and we excluded several important factors from the original HOMR model. These were substituted with new covariates, including the LAPS and life-table 1-year death risk estimates. This latter vital statistic from census data gave the model important individual patient prognostic information, which made up covariates unavailable at patient admission.

Several issues need to be considered when interpreting our results. While our findings are hopeful for being able to automatically generate an accurate prognosis for patients admitted to the hospital, the HOMR-now! model needs to be validated in other centers before it can be confidently applied externally. Second, it is unclear what effect providing a patient-specific survival estimate will have in patient care. It is possible that many hospital clinical decisions are made by physicians and patients without consideration of prognosis. This would be true if such decisions are being made for symptom control, in which case a patient's prognosis would not affect the decision. Alternatively, clinicians might be skeptical of a model that is missing many clinical factors that clinicians rely upon to generically prognosticate their patients and might therefore

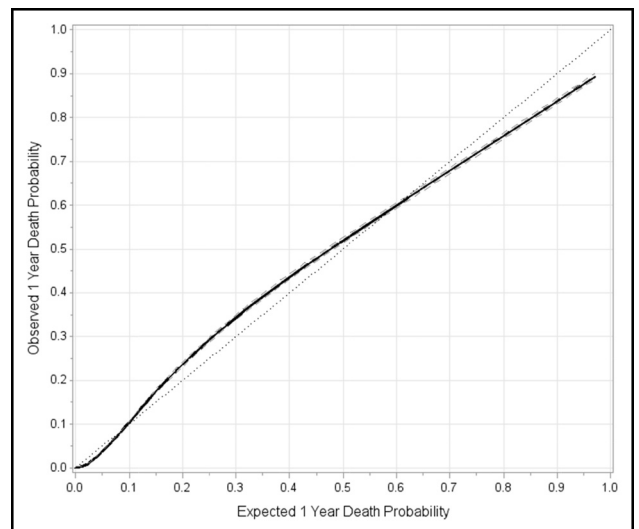


Figure 2 Observed vs expected 1-year death risk. The observed 1-year death probability (vertical axis) is plotted against the expected probability (horizontal axis). The heavy line presents the median value from 500 bootstrap samples and is flanked by the 2.5th and 97.5th credible interval (the latter is obscured by the median line in much of the plot). The unity line (dotted) represents perfect agreement between observed and expected risk.

not use the estimate. These are issues that should be addressed in future studies.

In summary, the HOMR-now! model used data from our hospital's data system to immediately and accurately predict 1-year death risk for our newly admitted patients. This model could serve as a framework for other hospitals to actively prognosticate hospitalized patients to help facilitate clinical decision-making.

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SUPPLEMENTARY DATA

Supplementary tables accompanying this article can be found in the online version at <http://dx.doi.org/10.1016/j.amjmed.2017.03.008>.

APPENDIX

Supplementary Table 1 The HOMR Score for Predicting 1-Year Death Risk When Adult Patients Are Admitted to the Hospital, Part A

Variable	Value	Points	Variable	Value	Points
Sex†	Female	0	ED visits*‡	0	0
	Male	1		1+	1
Home O ₂ §	No	0	Admissions by ambulance*‡	0	0
	Yes	4		1	3
Diagnostic risk score§				2	4
				3+	5
Service†	General medicine	10	Service	General surgery	8
	Cardiology	8		Cardiovascular surgery	9
	GI/Nephro/Neuro	9		Neurosurgery	10
	Palliative Care	28		Orthopedic, plastic surgery	7
	Hematology/Oncology	14		Thoracic/transplant	7
	Ante-, intra-, postpartum	0		Trauma	8
	Gynecology	7		Urology	6

ED = emergency department; GI = gastrointestinal; HOMR = Hospital-patient One-year Mortality Risk.

*In previous year.

†These variables could be replicated at patient admission with our hospital's data holdings.

‡These variables could be calculated but only using data holdings at our hospital.

§These variables could not be determined.

Supplementary Table 2 The HOMR Score for Predicting 1-Year Death Risk When Adult Patients Are Admitted to the Hospital, Part B

Variable	Level	Charlson Score Points						
		0	1	2	3	4	5	6
Age, y*	20-24.9	0	3	5	7	8	9	10
	25-29.9	2	5	7	9	10	11	11
	30-34.9	4	7	9	11	12	12	13
	35-39.9	7	9	11	12	13	14	15
	40-44.9	8	11	13	14	15	15	16
	45-49.9	10	13	14	15	16	17	17
	50-54.9	12	14	16	17	17	18	18
	55-59.9	14	16	17	18	19	19	20
	60-64.9	15	17	18	19	20	20	21
	65-69.9	17	19	20	21	21	22	22
	70-74.9	18	20	21	22	22	23	23
	75-79.9	20	21	22	23	23	24	24
	80-84.9	21	23	23	24	24	25	25
	85-89.9	23	24	25	25	25	26	26
	90-94.9	24	25	26	26	26	27	27
	95+	25	26	27	27	27	28	28

*This variable could be replicated at patient admission with our hospital's data holdings.

†This variable could be calculated but only using data holdings at our hospital.

Supplementary Table 3 The HOMR Score for Predicting 1-Year Death Risk When Adult Patients Are Admitted to the Hospital, Part C

Variable	Level	Admissions by Ambulance*‡			
		0	1	2	3+
Living status†	Independent	0	0	0	0
	Rehabilitation	3	3	2	2
	Home care	4	3	3	3
	Nursing home	4	4	4	3
Admission urgency†	Chronic hospital	8	6	5	5
	Elective	0	0	0	0
	ED, no ambulance	3	1	0	0
	ED, ambulance	5	2	1	0

ED = emergency department.

*In previous year.

†This variable could be replicated at patient admission with our hospital's data holdings.

‡This variable could be calculated but only using data holdings at our hospital.

Supplementary Table 4 The HOMR-now! Model

Variable	PE	95% Credible Interval
Intercept	-0.155	-0.880-0.699
Patient factors		
Male	-0.081	-0.113 to -0.046
ln (Death risk/[1-death risk])	0.541	0.521-0.583
Admitted before 2006	0.348	0.269-0.407
Max (Year admitted - 2010, 0)	-0.113	-0.135 to -0.100
Charlson+1	0.486	0.472-0.498
Living status		
Home	—	—
Rehab	0.722	-0.628-2.086
Nursing home	0.568	0.487-0.655
Chronic hospital	0.147	0.102-0.195
ln (ED visits last year + 1)	0.174	0.139-0.210
Seen in cancer clinic	0.402	0.326-0.467
Hospitalization factors		
Admission urgency		
Elective	—	—
ED, no ambulance	0.174	0.101-0.250
ED, with ambulance	0.425	0.351-0.507
Admission service		
Medicine	—	—
Cardiology	-0.817	-0.880 to -0.751
GI/Nephrology/Neurology	-0.297	-0.362 to -0.226
General surgery	-0.434	-0.493 to -0.366
Cardiovascular surgery	-0.358	-0.436 to -0.278
Neurosurgery	0.661	0.583-0.736
Orthopedics/plastics	-0.349	-0.420 to -0.290
Thoracic surgery	0.695	0.580-0.817
Trauma	0.727	0.645-0.804
Urology	-0.446	-0.568 to -0.329
Obstetrics	-3.097	-3.752 to -2.635
Gynecology	0.165	0.051-0.281
Hematology-Oncology	1.198	1.121-1.260
LAPS score + 1	0.019	0.018-0.019
1/(ED, no ambulance*Death risk/[1-death risk]+1)**2	-1.446	-1.928 to -0.780

Note that 1-year death risk was taken from population-based life tables.

ED = emergency department; GI = gastrointestinal; HOMR = Hospital-patient One-year Mortality Risk; LAPS = Laboratory-based Acute Physiological Score; PE = parameter estimate.