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The Hospital-patient One-year Mortality Risk score accurately predicted long-term death risk in hospitalized patients

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Abstract

Objective: Prognostication is difficult in a diverse patient population or when outcomes depend on multiple factors. This study derived and internally validated a model to predict risk of death from any cause within 1 year of admission to hospital.

Study Design and Setting: The study included all adult Ontarians admitted to nonpsychiatric hospital services in 2011 (n = 640,022) and deterministically linked administrative data to identify 20 patient and admission factors. A split-sample approach was used to derive and internally validate the model.

Results: A total of 75,082 people (11.7%) died within 1 year of admission to hospital. The final model included one dozen patient factors (age, sex, living status, comorbidities, home oxygen status, and number of emergency room visits and hospital admissions by ambulance in previous year) and hospitalization factors (admission service and urgency, admission to intensive care unit, whether current hospitalization was a readmission, and admission diagnostic risk score). The model in the validation cohort was highly discriminative (c-statistic 92.3), well calibrated, and used to create the Hospital-patient One-year Mortality Risk score that accurately predicted 1-year risk of death.

Conclusion: Routinely collected administrative data can be used to accurately predict 1-year death risk in adults admitted to nonpsychiatric hospital services.

Keywords: Risk model; Multivariable logistic regression; Risk score; Hospitalization; Discrimination; Calibration; Mortality; Administrative data; Risk index; Survival

1. Introduction

Given the multiple frequently correlated factors that influence mortality risk, it is not surprising that physicians find it difficult to estimate survival likelihood in particular patients. The correlation between clinician estimates and actual patient survival is low in cancer patients [1] in whom clinician survival predictions are usually optimistic [2–5] and inaccurate (despite highly accurate predictions of disease cure likelihood) [6]. Inaccurate physician prognostications have also been found in patients with congestive heart failure [7] and those admitted to the intensive care unit [8].

While physicians find it difficult to prognosticate in patients with a specific disease, one would expect it multiply difficult to do so in a diverse group of patients with an assortment of diseases. One such group is patients admitted to hospital, in which accurate estimation of mortality risk could serve three purposes. First, knowing the approximate probability of death within a year would allow patients and their physicians to make more informed decisions about their health care during the hospitalization and afterward. This could be especially relevant when deliberating interventions with no immediate influence on patient prognosis or symptoms. For example, patients with a high risk of death in the near future may choose to defer preventive treatments, screening interventions, or interventional procedures for presently asymptomatic conditions. Second, an accurate 1-year mortality risk assessment—especially if that risk is high—could motivate and inform discussions between patients and physicians regarding goals of care. Finally, an accurate model for 1-year mortality in admitted patients would provide an outcome by which health care performance could be compared between communities or hospitals.

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What is new?

Key finding

- The risk of death within 1 year of admission to hospital can be accurately estimated by a risk index (the Hospital-patient One-year Mortality Risk score) that quantifies the influence of a dozen patient and hospital factors to long-term survival.

What this adds to what was known?

- This finding shows that long-term mortality risk can be estimated in a diverse group of patients admitted to a hospital.

What is the implication and what should change now?

- The risk of death in 1 year for patients admitted to hospital can be estimated by determining the value of 12 factors.

At present, all options available for predicting death risk in patients admitted to hospital have limitations. Several studies have created multivariable models to predict risk of death *in hospital* in a broad assortment of patient populations [9−11]. Death in hospital is an important outcome, but variation in patient health status at hospital discharge—over time and between institutions—could make it a less reliable health indicator than longer term survival (which would be less sensitive to discharge thresholds). Population-based life tables provide extremely accurate 1-year survival estimates based on patient age and sex (and, in some countries, race) but do not account for patient severity of illness. Austin et al. derived and internally validated a model that used administrative data to predict 1-year survival in all—not just hospitalized—patients [12,13]. This model required the Johns Hopkins Adjusted Diagnosis Groups algorithm [14], which makes the model rather opaque (because we cannot know precisely how claims data get translated into Diagnosis Groups) and prohibits its use in real life. Long-term survival models have also been developed for patients with specific diseases such as congestive heart failure [15], acute myocardial infarction [16], and spinal cord injury [17].

In summary, no risk model is currently available to predict long-term survival in patients admitted to hospital. This study derived and internally validated such a model using administrative data.

2. Methods

This study used population-based health administrative databases in Ontario, Canada, in which the costs for all hospital and physician services are covered by a universal health care system. Databases used in this study included Discharge Abstract Database (DAD) that captures all hospitalizations; Registered Persons Database (RPD) that captures each person's date of death including those that occur out of province; Assistive Devices Program (ADP) that captures all patients on home oxygen; Continuing Care Reporting System (CCRS) that captures all registered nursing home and chronic hospital residents; Canadian Organ Replacement Register (CORR) that captures all patients on chronic hemodialysis; Same-Day Surgery (SDS) database that captures all encounters for surgical interventions in which patients are discharged from the institution on the same day as their intervention; Home Care Database (HCD) that captures all publicly funded in-home assistance; and the National Ambulatory Care Registry System (NACRS) that captures all visits to any emergency department (ED). All databases were linked deterministically via encrypted health care numbers. Details of the contribution of each database to the study are provided in Appendix A (see at www.jclinepi.com).

2.1. Study cohort

This study included all adult Ontarians with valid health card numbers who admitted to any acute-care hospital in Ontario between January 1 and December 31, 2011. This period was chosen because it was the latest calendar year for which data were complete for all people. Admissions to chronic hospitals or rehabilitation centers were not included. For people with more than one admission in 2011, one admission was randomly chosen to ensure that the study's unit of analysis was the person. Other admissions excluded from the study included those to psychiatric facilities (which are captured in a different database) and those for children aged <18 years of age (in whom the risk of death within 1 year is very low).

2.2. Study outcome

The outcome of the study was all-cause mortality within 1 year *of admission to hospital*. Outcome status was determined by linking to RPD.

2.3. Study covariates

The objective if the study was the prediction of mortality risk within 1 year of admission to hospital. Therefore, only variables whose value could be determined when a person was admitted to hospital, as well as those that were both clinically measurable and with a valid potential influence on patient survival, were considered for the study (see Appendix A at www.jclinepi.com). Patient age and sex were taken from DAD. DAD also provided the urgency of the index admission, admitting service, and whether the patient was admitted directly to the intensive care unit. All DAD encounters in the year before the patient's admission were used

to calculate the number of hospitalizations and hospital days (including, for both summary statistics, hospitalizations classified as urgent, those by ambulance, and total). All coded diagnoses in all admissions during the previous year (along with those for the index admission that were present when the patient entered the hospital) were used to identify patient comorbidities. End-stage renal disease requiring dialysis was identified by linking to CORR. Home oxygen status was determined from ADP. The total number of emergency room visits in the previous year (excluding those that resulted in admission to hospital) was determined from NACRS. Nursing home, retirement home, and chronic hospital status were determined from DAD and CCRS. Each patient's status regarding home-based nursing services or other assistance was determined from DAD and HCD. Details for defining covariates in the model are given in Appendix A (see at www.jclinepi.com).

2.4. Analysis

The patient cohort was randomly divided into equally sized derivation and validation cohorts. In the derivation set, multivariable binomial logistic regression was used to determine the independent association of each covariate with all-cause mortality within 1 year of admission to hospital. Patient comorbidities were summarized using the Charlson Score [18] calculated with diagnostic codes from Quan [19] and weights from Schneeweiss [20]. Fractional polynomial methods were used to determine optimal transformations for continuous and count variables [21,22].

Multivariable binomial logistic regression modeling took place in four steps. The *first step* offered all covariates listed in Appendix A (see at www.jclinepi.com) to the model. Those that were associated with 1-year mortality with a P-value <0.0001 (after forward stepwise variable selection) were kept in the "initial model." This P-value criterion was used to help create a parsimonious model. The *second step* tested for important interactions (defined as interaction terms that had a P-value <0.0001 and resulted in an improved model c-statistic or at least a 5% decrease in the Hosmer–Lemeshow statistic) between patient age, patient comorbidities, admission urgency, living status, and number of admissions. These covariates were identified a priori as being particularly important for patient prognosis and likely to influence the effect of other covariates on outcomes. This model was called the "initial model with interactions." The *third step* accounted for varying outcome risk with particular admission diagnoses by calculating a "Diagnostic Risk Score." Most responsible diagnoses that had the same first three alpha numerics of the International Classification of Diseases, Tenth Revision, Canada (ICD-10-CA) code were grouped together ("diagnostic groups"). Within each diagnostic group, the ratio of the observed number of deaths to the expected number of deaths for that group (calculated using the initial model with interactions from the second step) was calculated and multiplied by 10. In diagnostic groups whose ratio had a z score [23] with a two-sided P-value <0.001, the Diagnostic Risk Score was calculated as the logarithm of the observed-to-expected ratio. All other diagnostic groups were assigned a Diagnostic Risk Score of 0. The *fourth step* created the final model by running a logistic model having all covariates and interactions from the second step plus Diagnostic Risk Score.

Model fit was determined by calculating discrimination and calibration. Because of the large sample size of the study, we used recommendations from Paul et al. [24] and divided the validation sample into groups of approximately 1,000 patients each and calculated within each group a standard Hosmer–Lemeshow statistic. Survival estimates from the final model were compared with age–sex stratified 1-year mortality estimates from 2009 Ontario life tables from Statistics Canada (the latest year for which life tables were available). Methods from Sullivan et al. [25] were used to modify the final model into a point system (the Hospital-Patient One-year Mortality Risk [HOMR] score) to facilitate the comparison of the relative influence of each covariate on death risk.

3. Results

In 2011, there were 1,109,709 inpatient separations from acute-care hospitals in Ontario. Of these, 469,687 (42.3%) were excluded from the study; 271,507 (24.4%) occurred in patients who had been admitted at another time during that year; 196,561 (17.7%) were for patients who were aged <20 years, and 1,819 (0.2%) were for patients who had been discharged from a psychiatry service.

This left 640,022 patients in our study cohort (Table 1). Patients were middle aged and were predominantly female, from the community, and without important coded chronic medical conditions. In the previous year, one or more visits to the ED, any SDS, or any hospitalization occurred in 44.9%, 20.1%, and 21.3% of patients, respectively. More than 60% of people were admitted to general medicine, general surgery, or obstetrics with about half of patients being admitted through the emergency room. The derivation (n = 319,531) and validation (n = 320,491) cohort was essentially identical (see Appendix B at www.jclinepi.com).

A total of 75,082 patients died within 1 year of admission to hospital (crude risk 11.7%), of which 29,464 (30.2%) occurred during the index hospitalization. People who died within the year, compared with those who survived, were notably older (median age 79 vs. 55), were more likely to be male (50.4% vs. 36.5%), require home oxygen (10.5% vs. 1.3%), and less likely to be independent (45.5% vs. 87.9%) or have no coded comorbidities (11.5% vs. 63.9%; Table 1). Patients who died also had notably more extensive hospital utilization in the previous year,

Table 1. Description of study cohort by survival status 1 year after admission to hospital

Variable	Value	Alive (*N* = 564,940)	Dead (*N* = 75,082)	Total (*N* = 640,022)
Median age (IQR)		55 (35–72)	79 (68–86)	59 (37–75)
Male		206,447 (36.5)	37,826 (50.4)	244,273 (38.2)
Living status	Independent	496,853 (87.9)	34,164 (45.5)	531,017 (83.0)
	Rehabilitation	745 (0.1)	368 (0.5)	1,113 (0.2)
	Home care	51,041 (9.0)	26,548 (35.4)	77,589 (12.1)
	Nursing home	15,449 (2.7)	13,179 (17.6)	28,628 (4.5)
	Chronic hospital	852 (0.2)	823 (1.1)	1,675 (0.3)
Charlson Score	0	361,211 (63.9)	8,633 (11.5)	369,844 (57.8)
	1–2	121,701 (21.5)	17,286 (23.0)	138,987 (21.7)
	3+	82,028 (14.5)	49,163 (65.5)	131,191 (20.5)
Chronic dialysis		3,838 (0.7)	1,646 (2.2)	5,484 (0.9)
Home oxygen		7,112 (1.3)	7,906 (10.5)	15,018 (2.3)
1 + ED visits, prior year		245,384 (43.5)	42,294 (56.4)	287,678 (44.9)
1 + ED visits by ambulance, prior year		61,464 (10.9)	20,804 (27.7)	82,268 (12.8)
1 + Same day surgeries, prior year		110,510 (19.5)	17,884 (23.9)	128,394 (20)
1 + Hospitalizations, prior year		103,584 (18.3)	32,848 (42.8)	136,432 (21.3)
1 + Urgent hospitalizations, prior year		80,754 (14.3)	30,472 (40.4)	111,226 (17.3)
1 + Hospitalizations by ambulance, prior year		40,964 (7.3)	19,375 (25.6)	60,339 (9.4)
Admitting service, medicine	General	157,033 (27.8)	43,693 (58.2)	200,726 (31.4)
	Cardiology	35,852 (6.3)	4,868 (6.5)	40,720 (6.4)
	GI/Nephro/Neuro	26,582 (4.7)	4,872 (6.5)	31,454 (4.9)
	Palliative care	155 (0.0)	4,844 (6.5)	4,999 (0.8)
	Hematology/Oncology	9,272 (1.6)	5,759 (7.7)	15,031 (2.3)
Admitting service, Surgery	General	66,859 (11.8)	3,627 (4.8)	70,486 (11.0)
	Cardiovascular	11,014 (1.9)	1,177 (1.6)	12,191 (1.9)
	Neuro	6,834 (1.2)	833 (1.1)	7,667 (1.2)
	Orthopedic	51,767 (9.2)	2,098 (2.8)	53,865 (8.4)
	Plastic	13,282 (2.4)	364 (0.5)	13,646 (2.1)
	Thoracic/Transplant	3,561 (0.6)	445 (0.6)	4,006 (0.6)
	Trauma	7,671 (1.4)	902 (1.2)	8,573 (1.3)
	Urology	19,710 (3.5)	1,287 (1.7)	20,997 (3.3)
Admitting service, Obstetrics/Gynecology	Ante-, intra-, postpartum	131,616 (23.3)	23 (0.0)	131,639 (20.6)
	Gynecology	23,732 (4.2)	290 (0.4)	24,022 (3.8)
Admission urgency	Elective	293,916 (52.0)	9,229 (12.3)	303,145 (47.4)
	ED, no ambulance	145,433 (25.7)	19,186 (25.6)	164,619 (25.7)
	ED, ambulance	125,591 (22.2)	46,667 (62.2)	172,258 (26.9)
Hospitalization urgent, within 30 days of previous		21,139 (3.7)	7,989 (10.6)	29,128 (4.5)
Admitted to the intensive care unit		38,753 (6.9)	8,884 (11.8)	47,637 (7.4)

Abbreviations: ED, emergency department; IQR, interquartile range.
Data are presented as *n* (%) otherwise mentioned.
Definitions for each variable are given in Appendix A (see at www.jclinepi.com).

were more likely to be admitted to general medicine or palliative care services, and were more likely to be admitted from the ED via an ambulance.

The initial model with interactions (see Appendix C at www.jclinepi.com) included all of the covariates in Table 1 except chronic dialysis, ED visits by ambulance, same-day surgeries, and urgent hospitalizations in previous year. Important interactions were found between patient age and Charlson Score; annual number of admissions by ambulance and admission urgency; and annual number of admissions by ambulance and living status.

The Diagnostic Risk Score is presented in Appendix D (see at www.jclinepi.com). There were 71 diagnostic groups with a 1-year death risk that deviated significantly from expected. Thirty-one diagnostic groups had significantly more deaths than expected with the top six being cardiac arrest, anoxic brain injury, brain cancer, adult respiratory distress syndrome, pancreatic cancer, and shock. Forty diagnostic groups had significantly fewer deaths than expected with the lowest risk being thyroid cancer, female genital prolapse, vertigo, and asthma. In the validation cohort, the Diagnostic Risk Score ranged from −22 to 12 (median: 0; interquartile range [IQR], −3 to 0) with 198,984 (62.1%) having a score of 0. The overall ratio of observed-to-expected numbers of deaths in patients with Diagnostic Risk Scores <0 (n = 94,469), 0 (n = 198,984), and >0 (n = 27,038), was 0.64, 0.96, and 1.48, respectively.

The Diagnostic Risk Score was highly significant in the final model (see Appendix E at www.jclinepi.com). The relative adjusted odds of death in 1 year increased 20%

when the diagnostic risk score increased by 1 unit. The adjusted odds of 1-year death in people with home oxygen were more than doubled. Only two admitting services (hematology and/or oncology and palliative care) had adjusted odds of death that were significantly worse than that for patients admitted to general medicine. The odds of death increased notably with age (Fig. 1A), with the impact of patient comorbidity (as gauged by the Charlson Score) decreasing as patients aged (the interaction term between these covariates was negative, see Appendix E at www.jclinepi.com). One-year mortality risk increased as people became both progressively more dependent on help or had a greater number of admissions to hospital by ambulance (Fig. 1B). The latter factor notably influenced death risk for different admission status (Fig. 1C): increases in the adjusted odds ratio for people admitted through the emergency by ambulance vs. those admitted electively were much greater in patients without hospital admissions by ambulance in the previous year.

In the validation cohort, the final model had excellent discrimination (c-statistic, 92.3; 95% confidence interval [CI], 92.2, 92.4). Discrimination remained excellent (c-statistic, 90.0; 95% CI, 89.8, 90.1) even after the removal of patients admitted to obstetrical services (in whom risk of death is low). In contrast, discrimination using mortality estimates from Ontario age- and sex-stratified life tables was significantly lower (c-statistic, 80.4; 95% CI, 80.2, 80.6). The final model was also very well calibrated, with a mean relative difference between observed and expected death risk of 2.0% (range 0.0–7.0%; Fig. 2). The Hosmer–Lemeshow statistic in the validation group was insignificant in 272 of 320 calibration groups (85%) indicating very good fit. In contrast, risk estimates based on age–sex life tables were extensively lower than observed risks (Fig. 2). When stratified by covariates in the model, model-based 1-year risk estimates fell within the 95% CIs of the observed risk for all levels of each covariate except Diagnostic Risk Score, patient age, and Charlson Score (Table 2).

The HOMR score is presented in Table 3. A one-point increase in the HOMR score represents the increased adjusted risk of death associated with being male rather than female. In the validation group, the median HOMR score was 25 (IQR, 12–36; range, −12 to 76). Table 3 highlights the prominent influence of admission service, patient age, and patient comorbidities (as measured with the Charlson Score) on mortality risk. Table 3 also shows that the influence of increasing comorbidity on mortality

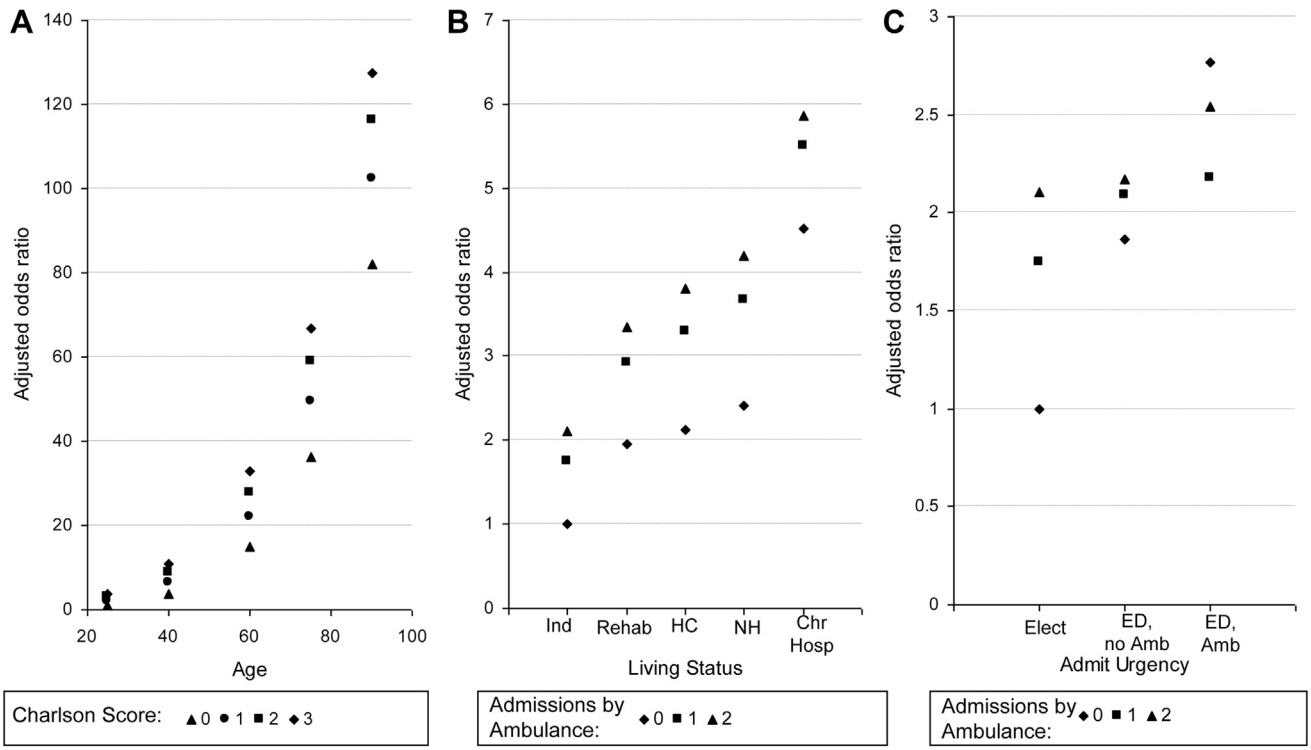

Fig. 1. Influence of interacting variables in final model with 1-year mortality risk. Each figure illustrates the independent combined influence of interacting covariates in the final model (see Appendix E at www.jclinepi.com) on the risk of death at 1 year. In each plot, one covariate is presented on the horizontal axis, whereas the other is defined in the legend. The vertical axis presents the adjusted odds ratio of death in 1 year relative to a reference group: (A) 25-year olds with Charlson Score of 0; (B) independent living person with no admissions by ambulance in the previous year; and (C) electively admitted patient with no admissions by ambulance in the previous year. Please note that each plot has a different scale. Chr Hosp, chronic hospital; ED, no Amb, through emergency department without ambulance; ED, Amb, emergency department with ambulance; Elect, elective; HC, home care; Ind, independent; NH, nursing home; Rehab, rehabilitation.

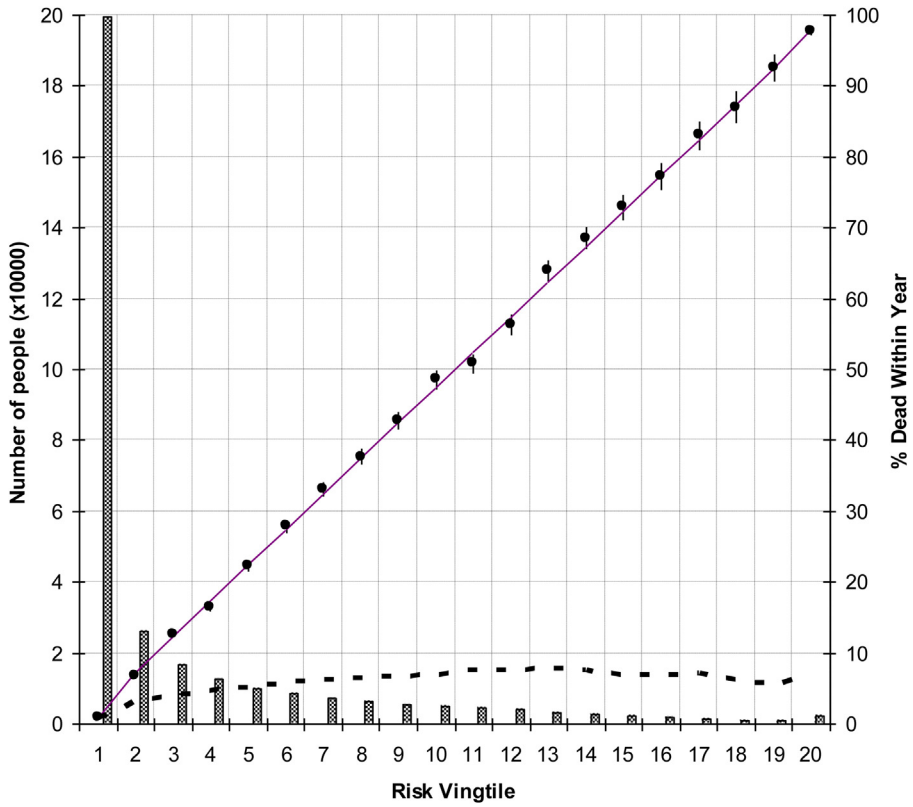

Fig. 2. Observed vs. expected risk of death within 1 year with population frequency. This plot presents all patients in the validation cohort categorized into 20 groups based on their expected risk of death within 1 year (horizontal axis) based on the final model (see Appendix E at www.jclinepi.com). The number of people within each group is presented (left vertical axis) along with the observed percentage of each group (with 95% confidence intervals) who died within 1 year of admission to hospital (right vertical axis). The solid line presents the model-generated expected percentage of people dying within a year. The dotted line presents the expected percentage of people dying within a year from population-based life tables.

risk decreased as patients aged and that the influence of both increasingly dependent living status and increasingly emergent admission urgency on mortality risk decreased as the number of hospital admissions by ambulance increased. In the validation group, the HOMR score had excellent discrimination (c-statistic, 91.72; 95% CI, 91.59, 91.85). Death risk started increasing notably when the HOMR score increased >30 with the model-generated expected risk of 1-year death for HOMR scores closely tracking observed death risk (Fig. 3).

4. Discussion

This article derived and internally validated a population-based model that accurately predicted 1-year death risk for people admitted to hospital. It found that the risk of any death within 1 year of admission to hospital could be estimated based on the value of a dozen easily quantified patient and hospitalization factors. This risk can be easily quantified using the HOMR score.

The most important finding of this study relates to the model's outcome, performance, breadth, and utility. In patients admitted to the hospital, the HOMR score predicted 1-year all-cause mortality, thereby avoiding error associated with assigning the cause of death (inherent in studies having cause-specific death as the outcome) and the transfer of preterminal patients from hospital to hospice (inherent in studies having death in hospital as the outcome). The model had exceptional discrimination and was very well calibrated for the entire study group (Figs. 2 and 3). The model was accurate in all important and disparate strata (Table 2) in a widely heterogenous group of patients (Table 1), suggesting that the HOMR score could be applied to all nonpsychiatric adult patients admitted to hospital. Given this wide applicability, the HOMR score could aid in measuring health system performance by adjusting 1-year mortality risk in hospital patients in different hospitals or communities. Such analyses could help identify areas or facilities with notably better or worse 1-year survival to determine factors that might, respectively, positively or negatively influence patient outcomes. The model's performance should be validated in populations in which it is used.

Several aspects of the model and its potential applications deserve comment. First, the use of population-based

Table 2. Observed vs. expected risk of death in 1 year in validation group in subgroups

Variable	Level	*N*	Percent dead within year	
			Observed (95% CI)	Expected
Diagnostic Risk Score	<0	94,469	7.2 (7.0, 7.4)	6.7
	0	198,984	8.5 (8.4, 8.6)	9.4
	>0	27,038	50.7 (50.1, 51.3)	46
Age	<28	27,759	0.4 (0.3, 0.5)	0.2
	28–34	41,805	0.4 (0.3, 0.5)	0.3
	35–59	93,094	4.6 (4.4, 4.7)	4.4
	60–74	74,106	12.7 (12.5, 13.0)	13.3
	75–84	51,738	22.3 (22.0, 22.7)	23.2
	85+	31,989	37.4 (36.8, 37.9)	35.2
Sex	Female	198,197	9.4 (9.3, 9.5)	9.4
	Male	122,294	15.4 (15.2, 15.6)	15.4
Living status	Independent	266,115	6.5 (6.4, 6.6)	6.4
	Rehabilitation	574	34.0 (30.1, 37.8)	32.8
	Home care	38,627	33.8 (33.3, 34.2)	34.1
	Nursing home	14,354	46.0 (45.2, 46.8)	46.2
	Chronic hospital	821	49.2 (45.8, 52.6)	51.1
Charlson Score	0	185,149	2.3 (2.3, 2.4)	2.0
	1–2	69,793	12.5 (12.2, 12.7)	12.9
	3+	65,549	37.3 (37.0, 37.7)	37.6
Home oxygen	Absent	313,012	10.7 (10.6, 10.8)	10.7
	Present	7,479	51.8 (50.7, 52.9)	52.2
ED visits in previous year	0	176,494	9.3 (9.1, 9.4)	9.2
	1	70,918	13.2 (12.9, 13.4)	13.3
	2+	73,079	16.1 (15.8, 16.3)	16.1
Admissions by ambulance in previous year	0	290,184	9.6 (9.5, 9.7)	9.6
	1	22,054	29.3 (28.7, 29.9)	29.6
	2+	8,253	38.8 (37.8, 39.9)	38.0
Admitting service	General medicine	100,418	21.7 (21.4, 21.9)	21.7
	Ante-, intra-, postpartum	65,886	0 (0)	0
	General surgery	35,376	5.2 (5.0, 5.5)	5.0
	Orthopedic surgery	26,864	3.8 (3.5, 4.0)	4.0
	Cardiology	20,478	11.9 (11.5, 12.4)	11.9
Admission urgency	Elective	151,778	3.0 (2.9, 3.1)	3.1
	ED, no ambulance	82,358	11.5 (11.3, 11.7)	11.7
	ED, ambulance	86,355	27.1 (26.8, 27.4)	26.8
Hospitalization was urgent and within 30 days of previous	No	305,970	10.9 (10.8, 11.1)	11.0
	Yes	14,521	27.6 (26.8, 28.3)	26.9
Patient admitted directly to intensive care unit	No	296,712	11.1 (11.0, 11.2)	11.1
	Yes	23,779	18.7 (18.2, 19.2)	18.5

Abbreviations: CI, confidence interval; ED, emergency department.

The table presents the observed and expected risk of 1-year death in specific subgroups. For each strata, the observed (with 95% CI) and expected risk of 1-year death is presented.

administrative data ensured that the study contained a complete inception cohort and captured all outcomes (two of the most important qualities for unbiased prognostic studies [26]). Second, the covariates included in the model are transparent and readily applicable in real life. However, before the model is used for front-line decision making, its performance should first be validated using primary data. This is especially relevant because two of the covariates in the model—Charlson comorbidity score and the Diagnostic Risk Score—relied on ICD-10 diagnostic codes, each of which will have variable accuracy for the true condition that they purportedly represent. Because the coding of comorbidities in administrative data is frequently incomplete [27,28], it is possible that this model underestimates the influence of comorbidities on death risk. For example, Kieszak et al. [27] found relatively poor agreement between comorbidities identified at chart review with those that were coded (with the latter being much less prevalent than the former); in addition, the adjusted association between the Charlson Score and hospital mortality was 10.0 and 2.1 when Charlson Score was calculated using chart review or codes, respectively. Third, although the Diagnostic Risk Score was strongly associated with death risk (see Appendix E at www.jclinepi.com), some of the individual diagnoses within particular diagnostic groups likely have death risks that are distinct from others in that group. For example, the diagnostic group of shock (all most responsible diagnoses whose codes start with "R57") has a Diagnostic Risk Score of 8 points. However, one of the component diagnoses is hypovolemic shock (R571,

Table 3. Hospital-patient One-year Mortality Risk (HOMR) scoring system

Variable	Value	Points
Sex	Female	0
	Male	1
Home oxygen	No	0
	Yes	4
Diagnostic Risk Score[a]		Same
Patient admitted directly to ICU		2
Urgent 30-day readmission		1
Service[b]	General medicine	10
	Cardiology	8
	GI/Nephro/Neuro	9
	Palliative care	28
	Hematology/Oncology	14
	Ante-, intra-, postpartum	0
	Gynecology	7
	General surgery	8
	Cardiovascular surgery	9
	Neurosurgery	10
	Orthopedic, plastic surgery	7
	Thoracic/Transplant	7
	Trauma	8
	Urology	6
ED visits in previous year	0	0
	1+	1
Admissions by ambulance[c]	0	0
	1	3
	2	4
	3+	5

		Points						
		Charlson Score						
Variable	Level	0	1	2	3	4	5	6
Age	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

		Points			
		Admissions by ambulance			
Variable	Level	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
	Chronic hospital	8	6	5	5
Admission urgency	Elective	0	0	0	0
	ED, no ambulance	3	1	0	0
	ED, ambulance	5	2	1	0

Abbreviations: ED, emergency department; ICU, intensive care unit.

The patients HOMR score is the sum of points assigned to each covariate. The Diagnostic Risk Score measured the risk of death in 1 year for diagnostic clusters independent of the other factors in the model. In the validation cohort, the Diagnostic Risk Score ranged from −22 to +12 (median: 0; interquartile range: −3 to 0) and can be determined from Appendix B (see at www.jclinepi.com). The risk of death in 1 year of admission to hospital for each HOMR score can be abstracted from Fig. 3. Note that points for interacting covariates age and Charlson Score include risk from patient age, Charlson Score, and the interaction of these covariates. The points for living status and admission urgency include risk for these covariates and their interaction with admissions by ambulance in the previous year; points for the latter covariate are considered separately at the top of the table.

[a] See Appendix D at www.jclinepi.com.

[b] See Appendix A at www.jclinepi.com for definitions of each service value.

[c] In previous year.

constituting 6.2% of this diagnostic group) which is prognostically much less ominous than either of the primary components of the diagnostic group (septic shock [R572] or cardiogenic shock [R570]). Further work could be done to modify the diagnostic risk groups to contain component diagnoses with similar death risks. Fourth, because the model excluded the pediatric population, its applicability to these patients is uncertain. Fifth, our study could have missed some deaths, because of emigration or other reasons, but it is unlikely that the error introduced by this would change the study's results in any meaningful way. Finally, because it was derived using administrative data, the model does not contain potentially important clinical prognosticators that are either non–disease specific (such as performance status, anorexia, and weight loss [1]) or disease specific (such as ejection fraction in congestive heart failure [29], FEV1 in chronic obstructive lung disease [30], or cancer stage). However, the HOMR score could serve as a foundation for the development of disease-specific risk scores. This could be necessary, because the performance of the HOMR score could decrease when it is applied to a focused cohort of patients who have the same disease. This phenomenon has been seen previously when a non–disease-specific risk index is applied to a more focused patient population [31,32] and occurs because similar patients tend to have similar risk scores, resulting in a decrease in the model's discrimination.

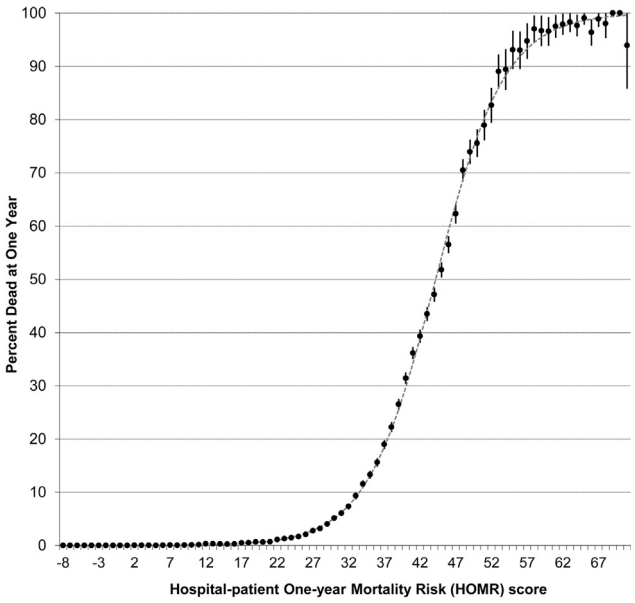

Fig. 3. Observed and expected probability of death by Hospital-patient One-year Mortality Risk (HOMR) score. The horizontal axis presents the HOMR score. The vertical axis presents the percentage of patients who died within 1 year of admission to hospital. For each score, the observed percentage of patients in the validation group who died within 1 year of admission to hospital is presented using black dots (with 95% confidence intervals). The expected percentage dead at 1 year is presented as the gray dotted line.

In summary, this study presents a model that uses administrative data to accurately predict the risk of 1-year death in a broad range of patients admitted to hospital. If validated in other health care systems, this could be used to measure, monitor, and compare health system performance. If validated in data collected from primary sources, it could help patients and physicians make better informed decisions regarding health care.

Appendix

Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jclinepi.2014.05.003.

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