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A clinical prediction tool for hospital mortality in critically ill elderly patients☆,☆☆

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ABSTRACT

Background: Very elderly (80 years of age and above) critically ill patients admitted to medical intensive care units (ICUs) have a high incidence of mortality, prolonged hospital length of stay, and living in a dependent state should they survive.
Objective: The objective was to develop a clinical prediction tool for hospital mortality to improve future end-of-life decision making for very elderly patients who are admitted to Canadian ICUs.
Design: This was a prospective, multicenter cohort study.
Setting: Data from 1033 very elderly medical patients admitted to 22 Canadian academic and nonacademic ICUs were analyzed.
Interventions: A univariate analysis of selected predictors to ascertain prognostic power was performed, followed by multivariable logistic regression to derive the final prediction tool.
Main results: We included 1033 elderly patients in the analyses. Mean age was 84.6 ± 3.5 years, 55% were male, mean Acute Physiology and Chronic Health Evaluation II score was 23.1 ± 7.9, Sequential Organ Failure Assessment score was 5.3 ± 3.4, median ICU length of stay was 4.1 (interquartile range, 6.2) days, median hospital length of stay was 16.2 (interquartile range, 25.0) days, and ICU mortality and all-cause hospital mortality were 27% and 41%, respectively. Important predictors of hospital mortality at the time of ICU admission include age (85-90 years of age had an odds ratio of hospital mortality of 1.63 [1.04-2.56]; >90 years of age had an odds ratio of hospital mortality of 2.64 [1.27-5.48]), serum creatinine (120-300 had an odds ratio of hospital mortality of 1.57 [1.01-2.44]; >300 had an odds ratio of hospital mortality of 5.29 [2.43-11.51]), Glasgow Coma Scale (13-14 had an odds ratio of hospital mortality of 2.09 [1.09-3.98]; 8-12 had an odds ratio of hospital mortality of 2.31 [1.34-3.97]; 4-7 had an odds ratio of hospital mortality of 5.75 [3.02-10.95]; 3 had an odds ratio of hospital mortality of 8.97 [3.70-21.74]), and serum pH (<7.15 had an odds ratio of hospital mortality of 2.44 [1.07-5.60]).
Conclusion: We identified high-risk characteristics for hospital mortality in the elderly population and developed a Risk Scale that may be used to inform discussions regarding goals of care in the future. Further study is warranted to validate the Risk Scale in other settings and evaluate its impact on clinical decision making.

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1. Introduction

The eldest sector of the population is growing faster than all other age groups, both in Canada and around the world [1,2]. In 1931, less than 60% of Canadian males and 62% of females survived to age 65 years, compared with 84% and 90% respectively, in 2001. The main causes of death in this demographic group were degenerative diseases and cancer [3]. Only 20% of these deaths occurred in Canadian intensive care units (ICUs) [4,5]. Currently, patients older than 65 years account for half of ICU admissions and nearly 60% of all ICU days [6–8]. This large change in our demographics is straining our health care system, in general, and critical care services, specifically. There is conflicting evidence regarding the effect of age on ICU mortality [9–14]. Meanwhile, it is known that elderly ICU patients can have very good survival [15–19].

Based on survey data from both Canada and abroad, most people would prefer to be cared for and to die in their own homes [5–7]. In addition, although 70% of elderly Canadian patients state a preference for comfort care over high-technology life-prolonging treatment in an inpatient setting, 54% are still admitted to ICUs [10–11]. More concerning was the fact that 57% of these respondents stated that they would decline a subsequent life-sustaining ICU admission in the event of a recurrent critical illness [12]. A 2006 study by Heyland et al identified that elderly Canadians value quality, not quantity of life, and do not want technology-supported life-prolonging measures. Notwithstanding, intensivists in Canadian ICUs continue to provide mechanical ventilation and use life-prolonging technology in the elderly even when there is little chance of meaningful recovery. There is currently a significant disconnect between the wishes of the Canadian population and actual clinical practice. This discrepancy may disrespect patient autonomy and prolong the dying process at significant expense to the health care system.

Use of a clinical prediction tool can complement clinician judgment, enhance confidence in end-of-life decision making, optimize the alignment between goals of care and realistic clinical outcomes, and improve health care resource utilization. Our goal was to develop a clinical prediction tool using information available at the time of ICU referral. Our prediction tool for hospital mortality in critically ill elderly patients is derived from the largest prospective data set to date in this elderly population.

2. Methods

2.1. Design and setting

This is a secondary analysis of the Realities, Expectations and Attitudes to Life Support Technologies in Intensive Care for Octogenarians (REALISTIC-80) Study, clinicaltrials.gov NCT01293708, a multicenter (22 ICUs), prospective, observational cohort study conducted from September 2009 to February 2013. Waived consent was obtained from the Research Ethics Boards of all participating centers. All patients older than 80 years who were admitted to ICU were eligible.

2.2. Study population

We included a consecutive sample of all patients admitted to participating ICUs who were 80 years of age or older. Enrollment began in September 2009 and was completed in February 2013. Although data were gathered on medical, surgical emergency, and elective surgical patients, this study is focused exclusively on the medical patients. Outcomes and processes of care differed significantly between medical patients and their surgical counterparts. Surgical patients likely mandate a separate prediction tool. Previously enrolled patients who were readmitted to the ICU were not reenrolled, as comprehensive data collection continued for 12 months following the index ICU admission. Routine local practices for ICU admission were maintained.

2.3. Baseline data collection

Trained research personnel collected data on the following variables for each study participant: age, sex, marital status, living status, Acute Physiology and Chronic Health Evaluation (APACHE) II [20], Sequential Organ Failure Assessment (SOFA) [21], Functional Comorbidity Index [22], Charlson Comorbidity Index [23], admission type (medical, surgical emergency, surgical elective), admission after acute or chronic illness, length of hospital stay before ICU admission, primary ICU diagnosis, number of hospitalizations and emergency department visits in the preceding 12 months, serum albumin, body mass index, days in ICU and in hospital, days on invasive or noninvasive mechanical ventilation, use of vasoactive medications, renal replacement therapy, and survival. It was left at the discretion of individual sites whether to report the individual APACHE II components or the aggregate score. The Glasgow Coma Scale (GCS) component of the APACHE II score was based on the patients' scores before sedation. In the event that no unsedated scores were available, research personnel were asked to estimate an unsedated GCS.

Hospital survival was defined as being discharged from hospital, or alive in hospital up to 1 year after ICU admission. Early in the recruitment phase, funding permitted each site to enroll a convenience sample of the first 60 eligible patients. Because of funding constraints, this number was decreased to 30 patients per site partway through the study. A rule of thumb is that at least 10 outcomes are required for every predictor variable that is evaluated [10,24,25]. With an expected hospital mortality of at least 30%, an n of more than 1000 would provide 300 outcomes (deaths), which are adequate to evaluate a model comprised of 30 predictor variables.

2.4. Data analysis

We used mean, standard deviation, and ranges to summarize continuous variables and median, interquartile range, and ranges for skewed variables (eg, length of stay). Categorical variables were described by counts and percentages. The association between predictors and the primary outcome was assessed using univariable logistic regression. Continuous variables were categorized using the most clinically sensible discriminative cut points. Predictors associated with hospital mortality at a P value $< .2$ and widely available in most emergency departments or on hospital wards were included in the multivariable logistic regression model. We did not formally assess interobserver reliability of these predictor variables in the derivation phase.

Univariable analysis was used to evaluate the associations between predictor variables (APACHE II components) and the primary outcome (all-cause hospital mortality). Continuous variables were categorized based on discriminative ability and clinical sensibility. For example, age was categorized into 5-year intervals between 80 and 90, and then >90 because of the smaller population in this category. Statistical techniques for categorizing continuous variables are available [26], but we reasoned that use of practical cut points with strong discriminative capacity would be preferable. We performed multivariable logistic regression using predictor variables identified in the univariate analysis.

The preliminary mortality risk stratification scale consists of simple elements that are readily available in emergency departments and hospital wards. Historical elements were available from the patient, their chart, or their substitute decision maker; clinical elements were obtained from patient examination; and metabolic elements were derived from blood tests. The risk stratification scale was created by rounding up the lowest multivariable logistic regression β coefficient to 1, which then served as the lowest common denominator for assigning point values to the other predictor variables. The remaining β coefficients were divided by the lowest β coefficient value and rounded to the nearest integer value to obtain their Risk Scale scores [27,28].

SAS version 9.3 (SAS Institute, Cary, NC) was used for the statistical tests.