A Geriatric-Specific Morbidity and Mortality Risk Stratification Tool

Hayley Premo[1], Harvey Shi[1], Sai Harshith Rachakonda[2], Will Knechtle[3], Marshall Nichols[3], Michael Gao[3], Mark Sendak[3], Bradley Hintze[3], Suresh Balu[3], Shelley McDonald,DO/PhD[4], Jeanna Blitz,MD/FASA[5], Sandhya Lagoo-Deenadayalan, MD/PhD[6], Hadiza S Kazaure, MD[6]

[1] Duke University School of Medicine, [2]Duke University Trinity College of Arts and Sciences, [3]Duke Institute for Health Innovation, [4]Department of Medicine, Duke University Health System, [5]Department of Anesthesiology, Duke University Health System, [6]Division of Surgical Oncology, Duke University Health System

Background.

Older adults are a highly vulnerable patient population at increased risk of perioperative morbidity and mortality. As the mean age of the United States population rises, the ability of a surgeon to make decisions by accurately incorporating goals of care, the utility of surgery, and the risk of harm is becoming an increasing critical skill. Adults over the age of 65 account for nearly 40% of inpatient surgical procedures in the US, and their hospital stays often require heavy resource utilization[1-2]. To effectively identify which patients are too high risk for surgery, physicians require objective measures of the clinical factors that confer this elevated risk status. At present, there are no standardized geriatric-specific perioperative risk stratification tools that incorporate pertinent variables such as function, cognition, nutrition, polypharmacy, and code status. Here, we build upon Pythia, a pre-existing machine learning model used to predict complications with surgical procedures, by integrating geriatric-specific characteristics to generate a more accurate risk stratification for a given patient[3]. The model output will stratify a given patient into a risk category and identify those that need optimization, those who may not benefit from surgery, and those likely to experience perioperative morbidity and mortality.

Methods.

Model input data included all surgical patients and was curated from 218,016 encounters of 161,414 individual adults. Cohort inclusion criteria required a documented surgical case creation from January 01, 2016 to December 31, 2019 with a subsequent surgery ≤3 months from case creation date. The geriatric population was defined as patients aged ≥ 65 years and the final cohort meeting this criterion contained 81,130 encounters across 56,357 unique patients. The model incorporated 518 input features, including demographic characteristics, laboratory tests, vitals data, and comorbidities. To enhance the model for the geriatric population, we added pertinent variables that carry greater significance in the geriatric population, such as polypharmacy (defined as ≥5 active medications), Mini-Cognitive Assessment scores, Duke Activity Status Index (DASI) score, and MiniBEST (Balance Evaluation Systems Test). The model was designed to output data regarding morbidity and mortality. The primary outcome was defined as mortality ≤30 days of surgery. Additional outcomes included postoperative complications ≤30 days. Complications were defined on a systems-based level, using ICD9 and ICD9-matched ICD10 codes chosen after an extensive literature review. All complication categories are displayed in **Figure 1.** Models were evaluated using area under the receiver operating characteristic curve (AUROC) and area under the precision-recall operating curve (AUPRC).

Results.

The primary outcome of interest was 30-day perioperative mortality; this was 0.68% for the full dataset and 1.0% for the geriatric subset. AUROC measured 0.9162 and AUPRC measured 0.2904 for the geriatric cohort, and 0.9511 and 0.3479 for all surgical patients. Model performances for additional outcomes are reported in **Figure 1**.

Figure 1

Complication	AUROC	AUPRC
60 day mortality	0.9650	0.5936
Shock	0.9572	0.3797
Cardiac	0.9032	0.4171
Neurological	0.8640	0.1319
Integumentary	0.8595	0.1191
Pulmonary	0.8483	0.0588
Endocrine	0.8444	0.1979
Genitourinary	0.8411	0.1396
Hematological	0.8065	0.1201
Gastrointestinal	0.8309	0.0648
Renal	0.8001	0.0425
Vascular	0.7951	0.1128
Sepsis	0.7646	0.0705
Falls	0.7639	0.0090

Conclusion.

Initial development of a machine learning model with inclusion of geriatric-specific inputs demonstrated compelling results, indicating its potential as a clinically useful tool for risk stratification of older adults. Future efforts will include more specific identification of complications in the cohort, such as myocardial infarctions among cardiac complications, in order to delineate actionable outputs.

References.

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