NAPCRG 52nd Annual Meeting — Abstracts of Completed Research 2024.

Submission Id: 6049

Title

Identifying Patients at High Risk for Falls using an AI/ML model

Priority 1 (Research Category)

Geriatrics

Presenters

Kristina steinberg, MD, MMCi

Abstract

Context: Patient Safety Objective: Identify Patients at High Risk for Falls using an AI/ML model. Falls among elderly patients are costly and potentially preventable. Approximately $50 billion dollars are spent on medical costs related to falls in US older adults every year and fatal falls are on the rise. Overtreatment of hypertension has been identified as a major risk factor for putting patients at risk for falls in patients with low blood pressures. Historically, most fall risk mitigation efforts occur after the first fall. Evidence-based interventions have been aimed at this population. Given the prevalence of fall risk, it is not feasible for a primary care practice to implement an evidence-based risk reduction intervention on every patient before they fall. A risk assessment tool that proactively identifies a smaller cohort of patients at the highest fall risk of fall could provide primary care practices with the ability to implement meaningful fall mitigation efforts. Study Design: Secondary data analysis created a machine learning model that identified high risk patients potentially over treated for hypertension placing them at higher fall risk. We utilized Amazon Sagemaker Canvas to design our machine learning model. Model design Variables included: blood pressure values, medications, chronic conditions and history of fractures. Setting/Dataset: Database containing over 20 million patients. Population Studied: Patients over the age of 75 with hypertension and most recent systolic blood pressures below 100 mmHg systolic and diastolic 70mmHg. Intervention: Amazon Sagemaker Canvas Outcome Measures: Patients with a calculated fall risk score of greater than 80%. Results: Initial cohort included 264,634 people 75 and older; 18,465 had diagnosis of hypertension and at least one low blood pressure. Of the 18,465 patients, 2,739 were identified by the model of having a potential fall outcome (14%). Of these identified, 329 patients were deemed highest risk with a fall risk score greater than 80%. Fall rate of the entire population was 2.2% over 24 months. The odds ratio of a fall for the high-risk cohort was 5.1 (CI 3.4 – 7.5) Model performance metrics: area under the curve (AUC) 0.89, precision of 87.9 and accuracy of 88.2. Conclusion: We designed a well performing, machine learning algorithm that identifies an

addressable cohort of patients at high-risk for falls on whom an evidence-base intervention may be implemented.