intervention, a decolonization program would still result in cost-savings for society, the healthcare system and patients. **Conclusions:** In addition to health benefits of preventing infections, postdischarge decolonization of MRSA carriers yields substantial savings to society and the healthcare system. Future recommendations for reducing postdischarge MRSA-related disease among MRSA carriers should consider routine decolonization at hospital discharge.

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Presentation Type:
Oral Presentation

Data Mining to Guide a Program to Prevent Infection Related Readmissions From Skilled Nursing Facilities

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Background: Readmissions to hospitals are common, costly and often preventable, notably readmissions due to infections. A 30-day readmission analysis following hospital discharges, found much of the variation in Medicare spending between hospitals was related to readmissions and skilled nursing facility (SNF) care. Although some readmissions of patients with advanced disease are not preventable, efforts to decrease readmission are most effectively directed towards those patients with intermediate levels of a specific risk. A prediction model to identify patients at highest (or intermediate) risk of infection readmission will help healthcare administrators and providers to allocate appropriate resources. Hospitals should use electronic health record (EHR) data with modern data mining techniques to create more curated, sophisticated models as part of a comprehensive transitional care program. We propose using the risk estimates of a validated prediction model to notify stakeholders and develop readmission rate reports by SNF or discharging physician. **Methods:** We applied machine learning (ML) methods to predict the risk of 30-day readmission due to sepsis and pneumonia of patients discharged to SNF. We used our EHR data during 2012–2017 to train and data from 2018 to validate. We applied ML algorithms to data including logistic regression, random forest, gradient boosting trees, and support vector machine. Data from EDW and EPIC clarity tables were extracted and managed using SAS Base 9.4

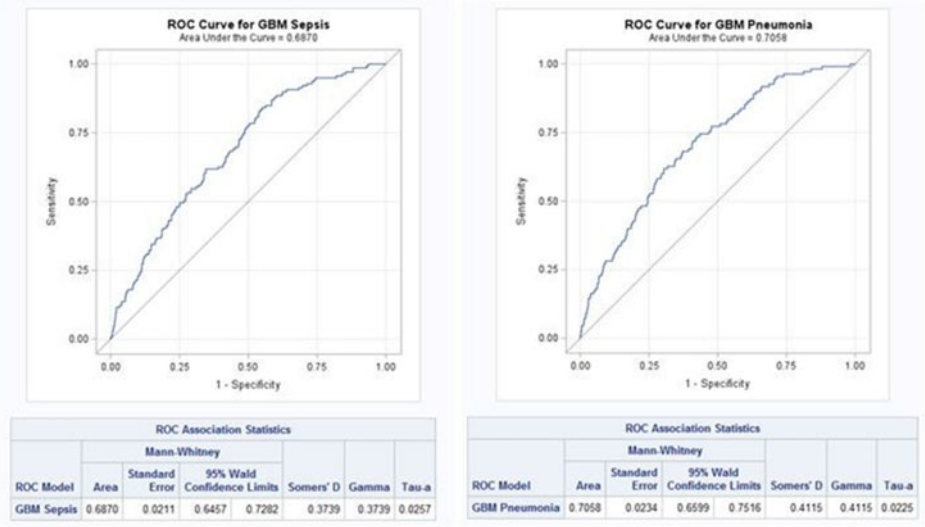

Figure 1. Area Under Receiver Operater Charcateristic curve for gradient boosting model predicting readmission after discharge to SNF due to sepsis and pneumonia

Fig. 1.

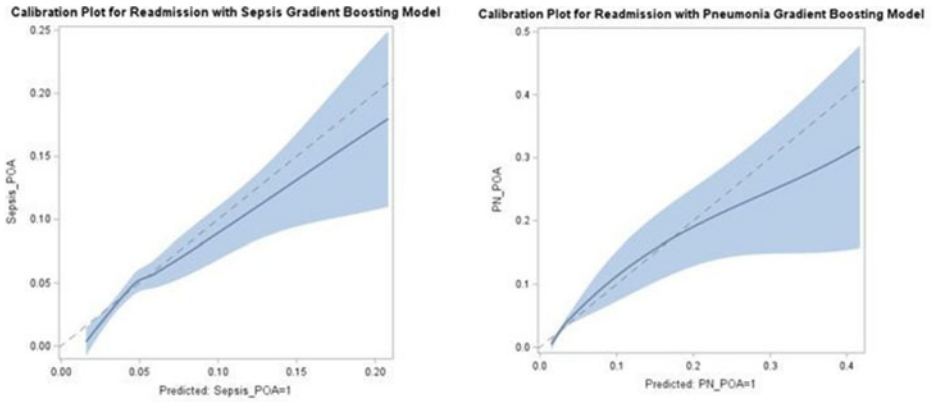

Figure 2. Calibration plot curves for gradient boosting model predicting readmission after discharge to SNF due to sepsis and pneumonia

Fig. 2.

and Enterprise Miner 14.3 (SAS Institute, Cary, NC). We assessed the discrimination and calibration to select the most effective prediction model. Using the resulted risk estimates, we created a notification system and reports for key stakeholders. **Results:** Figures 1 and 2 show the discrimination and calibration results of the final selected gradient boosting model (GBM). For predicting unplanned readmissions *with sepsis* and *with pneumonia* within 30 days after discharge to SNF, the c-statistic for final GBM model with 140 features was 0.69 (95% CI 0.65-0.73) and 73 features was 0.71 (95% CI 0.66-0.75), respectively. Table 1 lists features important to the validation set of the prediction model. We used estimates from these models to develop a daily email notification of patients discharged to SNF stratified into a low, medium, and high risk group for sepsis and pneumonia. We additionally created reports with case-mix adjustments to benchmark SNFs and discharging physicians to monitor and understand performance. **Conclusions:** Hospitals should leverage the plethora of data found in EHRs to curate readmission prediction models, and promote collaboration among transitional care teams and IPC to ultimately reduce readmissions due to sepsis and pneumonia.

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Table 1. Top 25 most important features for Sepsis and Pneumonia Gradient Boosting Model

Sepsis Features	Pneumonia Features
Acetic Acid	Albuterol Sulfate
Idarucizumab	Cefepime
Apixaban	Low Body Temperature
Normal Potassium Results	High Platelet Count
Furosemide	Circulatory disorder diagnosis in problem list
Vancomycin	Charlson Comorbidity Score
Diatrizoate Meg-Diatrizoat	High Neutrophil Absolute Count
Potassium Chloride	Renal Disease
Adenosine (Diagnostic)	Cerebrovascular Disease
Vancomycin	Presence Of Invasive Device
Insulin	Pulse Oximetry
Piperacillin-Tazobactam	Azithromycin
Digestive disease diagnosis in problem list	Haloperidol Lactate
Sulfamethoxazole-Trimethoprim	Congenital disorder diagnosis in problem list
Ephedrine Sulfate	Insertion Of Intralum Dev Into Inf Vena Cav
Dexamethasone	Chronic Pulmonary Disease
Respiratory diseases in problem list	Abemaciclib
Portable X-Ray administered	Injury Diagnosis
Ferrous Sulfate	Aclidinium Bromide
Low BMI	Number Of Medication Classes
Adenosine	Digestive disorder diagnosis in problem list
5-Hydroxytryptophan	Length Of Stay
Desflurane	White Blood Cell Value
Introduction of Nutritional into Up GI	Oncology Service

Presentation Type:
Oral Presentation

Detection of Possible Medical Product-Related Infection or Pathogen Transmission—United States, 2015–2019

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Background: Medications, medical devices, biological products, and other medical products can cause healthcare-associated infections related to contamination in production or transportation (intrinsic contamination) or contamination at the point of use (extrinsic contamination). Rapid identification of contaminated medical products can lead to actions to decrease further patient harm. We sought to describe events that prompted public health investigations of contaminated medical products in healthcare facilities. **Methods:** We reviewed records of CDC consultations with health departments and healthcare facilities from January 2015 through August 2019 to identify public health investigations in which medical products were identified as a likely source of patient infection or pathogen transmission to at least 1 patient. We collected data on products, contamination type, pathogens, route of patient exposure, healthcare setting where exposure occurred, and resulting actions. **Results:** There were 34 investigations involving medications (n = 15, 44%), medical devices (n = 12, 35%), biological products (n = 3, 9%), and other medical products (n = 4, 12%). Intrinsic contamination was suspected in 15 investigations (44%), with 13 (87%) based on isolation of a pathogen from unopened products and 2 (13%) based on isolation of similar pathogens from patients in contact with a medical product at multiple facilities. Extrinsic contamination was suspected in 19 investigations (56%) based on evidence of pathogen transmission at a single healthcare facility and concurrent infection control gaps at that facility supporting a mechanism of contamination. The most common pathogens prompting investigation were nontuberculous mycobacteria (n = 9, 26%), *Burkholderia* spp (n = 7, 21%), *Klebsiella* spp (n = 3, 9%), *Serratia* spp (n = 2, 6%), and other environmental and commensal organisms. Patients were most commonly exposed in hospitals (n = 19, 56%) and outpatient settings (n = 9, 26%). The most common patient exposures that resulted in transmission of the pathogen were infusions and injections (n = 15, 44%), diagnostic and therapeutic procedures (n