Presentation Type:
Poster Presentation - Top Poster Abstract
Subject Category: Dialysis
Candida auris Response in a Tennessee Dialysis Facility, 2023
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Background: Candida auris, a multi-drug resistant fungal pathogen, was introduced to Tennessee in 2021. There are limited studies on the spread of C. auris in highly specialized care settings including outpatient dialysis facilities. Facilities are concerned that C. auris transmission is difficult to prevent in this setting due to patient vulnerability, treatment frequency and length, and isolation challenges. As a result, these facilities may reject patients based on their positive colonization status. In 2023, the Tennessee Department of Health (TDH) conducted two containment-driven colonization screenings in response to a colonized patient receiving dialysis treatment for one month without their status being known to the facility. **Methods:** An initial point prevalence survey (PPS) was conducted to assess for ongoing transmission among dialysis patients. Patient screening was prioritized for the cohort of patients who received dialysis at the same time as the index patient (Cohort A). The screening was broadened to include patients dialyzed directly before Cohort A (Cohort B) by request of the Cohort B patients. A second PPS was conducted 7 weeks later, targeting the same cohorts. Specimens were collected through supervised patient self-collection of a skin swab from the axilla and groin. Flocked Eswabs were used for collection and transferred in Amies transport media to the Tennessee State Public Health Lab. The presence of C. auris was detected via Polymerase Chain Reaction (PCR). **Results:** Twenty-three patients (12 from Cohort A; 11 from Cohort B) were screened in the first PPS. One patient from Cohort A tested positive. This colonized patient was determined to be a known C. auris case first detected four months prior, but the patient's status was never communicated to the dialysis facility from the discharging acute care facility. Eleven patients, excluding the previously identified positives, participated (9 from Cohort A; 2 from Cohort B) in the second PPS; no positives were identified. **Discussion:** The index patient and an additional patient identified by the PPS both received dialysis at this facility for up to 4 months without facility knowledge. These results suggest that the standard infection control practices at this dialysis facility were adequate to prevent the transmission of C. auris among dialysis patients on multiple shifts. Additionally, patient self-collection identified a known C. auris patient. Future TDH work includes further evaluating the risk of C. auris transmission and developing targeted infection prevention and control practices for the outpatient dialysis setting.

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Presentation Type:
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Subject Category: Infection Prevention in Low and Middle-Income Countries
Rapid Scale-Up of Screening for Early Detection of Sudan Virus Disease (SVD) in Healthcare Facilities (HCFs) during the 2022 Outbreak in Uganda
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Background: The Uganda Ministry of Health (MoH) and implementing partners instituted an infection prevention and control (IPC) response strategy during the Uganda SVD outbreak in 2022 that involved rapid enhancement of screening capacity at HCFs. Rapid scale-up of screening for infectious diseases, such as SVD, is critical for early identification and triage of suspected or confirmed cases in HCFs. We describe the rapid deployment of a multimodal IPC strategy implemented in response to the SVD outbreak and the resulting impact on screening measures at HCFs. **Methods:** We implemented a multimodal IPC strategy in HCFs from five high risk districts to improve screening practices from November 2022–January 2023. The strategy included training health workers (HCWs) identified as IPC mentors; establishing screening areas; and providing screening supplies and communication materials. The three-day training utilized an MoH standardized training package with didactic and practice sessions. The mentors then cascaded screening information and skills to other HCWs through onsite trainings and mentorships and established screening areas. Baseline and endline (3 months after baseline) cross-sectional assessments were conducted using the MoH IPC Assessment Tool adapted from the WHO Ebola IPC Scorecard. The five main screening parameters assessed included presence of $\geq$ 1 meter distance between screener and the person screened, availability of a functional handwashing facility and infrared thermometer, correct record of each person's temperature, and appropriate referral process for those suspected of having SVD to holding areas. IPC capacity was measured through the summation of each of these parameter results and calculated as an overall percentage. IBM SPSS Statistics 20 software was used for data analysis and a paired t-test done to determine any significant findings between mean scores (percentage) at baseline and endpoint. **Results:** A total of 296 IPC mentors were trained, screening information was cascaded to 3,899 HCWs, and screening areas were established in 1,135 HCFs. Based on the screening results from the MoH IPC assessment tool, capacity improved from 44% (SD=37) at baseline to 67% (SD=34) at endpoint. Screening capacity improved from baseline to endpoint among level II and public HCFs from 33% (SD=35) to 60% (SD=35) ($p < 0$ .05) and from 54% (SD=38) to 76% (SD=31) ($p < 0$ .05), respectively. **Conclusion:** Rapid implementation of a multimodal IPC strategy was successful in enhancing screening capacity across Uganda's HCFs during a SVD response, which is critical for early identification of infected patients to interrupt transmission. This multimodal approach should be recommended for future response actions.

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Poster Presentation - Top Poster Abstract
Subject Category: Medical Informatics
Natural Language Processing (NLP) Accurately Identifies LTCF Exposure from Clinical Notes: A Proof-of-Principle Study
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Background: Residence or recent stay in a long-term care facility (LTCF) is one of the most important risk factors for multidrug-resistant organism (MDRO) carriage and infection, making reliable identification of LTCF-exposed inpatients a critical priority for infection control day-to-day practice and research. However, because most hospital electronic health records

(EHRs) do not include a dedicated field for documenting LTCF exposure, absent manual review of patient charts, identifying LTCF-exposed inpatients is challenging. We aimed to develop an automated, natural language processing (NLP)-based classifier for identifying LTCF exposure from clinical notes. **Methods:** We randomly sampled 1020 adult admissions from 2016-2021 across the 12-hospital University of Maryland Medical System and manually reviewed each admission's history & physical (H&P) note for mention of LTCF exposure (Figure 1). After H&P pre-processing, we calculated feature representations for documents based on term frequencies and visually explored between-group (LTCF-exposed vs. LTCF-unexposed) feature differences. To predict LTCF status from the H&P notes, we trained and tuned a LASSO regression-based classifier on 70% of the data with 3-fold cross-validation and 1:1 up-sampling to address class imbalance. The final classifier was evaluated on the 30% held-out sample (not up-sampled), with calculation of the C-statistic (area-under-the-curve, AUC) with bootstrapped 95% confidence intervals, and construction of receiver-operating-characteristic and variable importance plots (R Version 4.3.2). **Results:** 7% (n=76 cases) of H&P notes documented LTCF exposure. In our visual analysis, the H&P words and phrases that were over-represented among LTCF patients had high face validity (Figure 2). The final LASSO-regression-based classifier achieved a C-statistic of 0.89 (95% CI: 0.80–0.98) on the held-out data for identifying LTCF exposure from the H&P notes (Figure 3). The most important model predictors (i.e., words) for distinguishing LTCF-exposed from LTCF-unexposed patients are reflected in Figure 4. The most important predictor-words of LTCF-exposure were "rehab," "place," "status," "egd," and "dementia." **Conclusion:** In this multi-center study, even a simple NLP classifier demonstrated very strong discrimination for identifying LTCF exposure status from H&P notes, which could substantially reduce the manual review time required to identify LTCF-exposed inpatients. If automated in the electronic health record, it could also inform real-time MDRO screening decisions. Future research is planned to build more sophisticated classifiers using machine learning best practices, to build classifiers for additional MDRO risk factors, and to externally validate NLP classifiers on notes from an external healthcare system.

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Figure 1. Definition of Long-term Care Facility (LTCF) Exposure Documented in the History & Physical (H&P) Clinical Note

Mention of residence or stay in:
- Long-term care facility
- Skilled nursing facility (SNF)
- Assisted living facility (ALF)
- Rehabilitation facility
- Chronic facility
- "Other subacute" facility
- Facilities for patients with severe cognitive deficits who need assistance with ADLs

Timing:
That is estimated to have occurred within the preceding 90 days or description of the patient as an LTCF resident

Abbreviations: LTCF, long-term care facility; H&P, history and physical; ADL, activities of daily living.

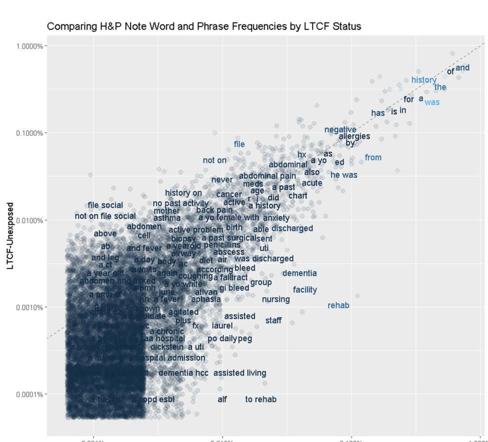
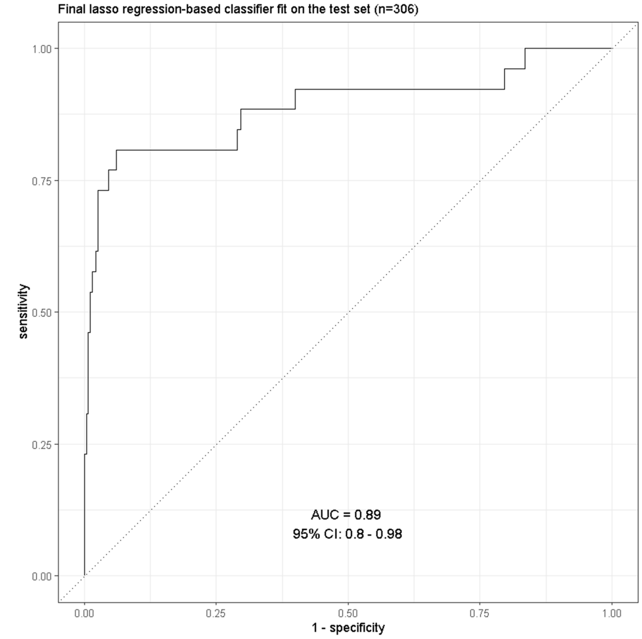


Figure 2. Plot of metrics for tokens from H&P notes of 1020 randomly sampled adult patients admitted to the University of Maryland Medical System between 2016-2021, stratified by LTCF exposure status. Tokens represent one- to four-grams (single words through four-word consecutive phrases). Tokens close to the dotted line occurred at similar proportions in the notes of LTCF-exposed and – unexposed patients. The further from the dotted line, the more over-represented a token is among LTCF-exposed (X-axis) (e.g., "rehab," "facility," "dementia") or LTCF-unexposed (Y-axis) patient notes. Tokens in the bottom left corner are infrequent among all notes. Tokens in the top right corner are common among all notes.

Figure 3. Receiver-Operating-Characteristic (ROC) Curve
Final lasso regression-based classifier fit on the test set (n=306)



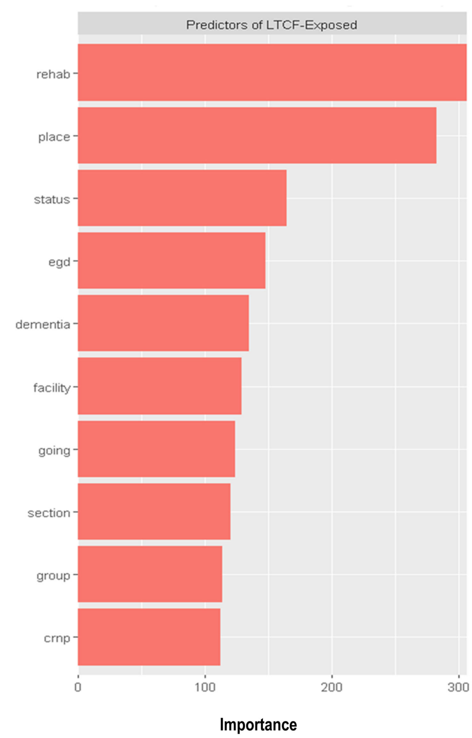


Figure 4. Variable importance plot of the most important predictor-words of LTCF exposure in H&P notes from a lasso regression-based NLP classifier.