

184 (31%) in Eldoret and 55 of 190 (29%) in Mombasa. Metronidazole was the next most commonly prescribed antibiotic (15%–19%). Meropenem was the only carbapenem reported: 22 of 387 patients (6%) in Nairobi, 2 of 190 patients (1%) in Eldoret, and 8 of 184 patients (4%) in Mombasa. Stop dates or review dates were not indicated for 106 of 390 patients (27%) in Nairobi, 75 of 190 patients (40%) in Eldoret, and 113 of 184 patients (72%) in Mombasa receiving antibiotics. Of 761 antibiotic prescriptions, 45% had a least 1 missed dose. Culture and antibiotic susceptibility tests were limited to 50 of 246 patients (20%) in Nairobi, 17 of 124 patients (14%) in Eldoret, and 23 of 119 patients (19%) in Mombasa who received antibiotics. The largest hospital had an administratively recognized antimicrobial stewardship committee.

Conclusions: The prevalence of antibiotic use found by our study was 46%, generally lower than the rates reported in 3 similar studies from other African countries, which ranged from 56% to 65%. However, these survey findings indicate that ample opportunities exist for improving antimicrobial stewardship efforts in Kenya considering the high usage of empiric therapy and low microbiologic diagnostic utilization.

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Poster Presentation

Postintra-vitreal Injection Endophthalmitis: An Infection Control Investigation and Case–Control Analysis of Risk Factors

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Background: Intravitreal injection of vascular endothelial growth factor inhibitors with or without steroids is a well-established, effective therapy for several ocular disorders. The expected rate of complications from these injections is low, with meta-analyses reporting 5–6 occurrences of infectious endophthalmitis per 10,000 injections. Through October 2019, our health system observed 8 cases of endophthalmitis among 7,693 injections (10.4 per 10,000 injections), compared to 1 case in 2018. This unusually high rate prompted an infection control investigation and a case control study to examine risk factors for the development of postintra-vitreal injection endophthalmitis. **Methods:** Infection control providers performed direct observation of several ophthalmologists performing intra-vitreal injections on 3 separate occasions to determine points of intervention to prevent infection. To define risk factors for postintra-vitreal injection endophthalmitis, we conducted a retrospective case-control study of the 8 affected patients. Four control patients were selected per case, matched by clinic location, drug injected, and date of injection (total subjects, $N = 40$). We extracted patient-level risk factors from medical records; documentation was not sufficient to compare procedure-level factors. We conducted unadjusted univariate Poisson regression and Mantel–Cox method rate ratios to identify significant risk predictors of endophthalmitis. **Results:** Direct observation yielded variable practice in use of masks, gloves, sterile lid speculum, and the duration of povidone-iodine contact on the ocular surface prior to injection. The

location of alcohol hand gel relative to the procedure field was sub-optimal. Due to patient volume, there were significant delays between procedure and patient prep and injection time. The mean age was 76 years among cases and 74.1 years among controls; 35% of patients were men. Age-related macular degeneration was the most common indication for injection (55%). Only 10% of injections were bilateral. Although not statistically significant, patients with coronary artery disease had a higher rate of infection than those without coronary artery disease (165.3 vs 16.3 per 10,000 person years; IRR = 3.0; 95% CI, 0.60–14.8; $P = .18$); current smokers were also at higher risk (86.9 per 10,000; IRR, 3.2; 95% CI, 0.33–30.4; $P = .32$). **Conclusions:** Coronary artery disease and smoking were risk factors for the development of postintra-vitreal injection endophthalmitis in a 2019 cluster of cases in our organization. We are continuing to work with our ophthalmologists to optimize infection prevention in the injection environment, including strict use of gloves, appropriate use of povidone-iodine, and routinely wearing a mask and encouraging a no-talking policy during injections.

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Practice Variation in Validation of Device Denominator Data for National Healthcare Safety Network Reporting

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Background: The NHSN is a widely used CDC program for tracking healthcare-associated infections (HAIs). The goal of the NHSN is to help healthcare organizations to identify and track the incidence of HAI and to prevent adverse events as well as to simplify mandatory quality reporting to the CMS. Healthcare organizations provide both event data for HAIs and information about the population at risk. For device-related infections, device denominator data (eg, data related to urinary or intravascular catheters, and ventilators) must be collected and reported. NHSN guidelines require that electronic reporting of device denominator numbers be validated to be within 5% of manually collected counts over a period of 3 consecutive months. Little is known about current practical application of validation practices. **Methods:** We surveyed members of the SHEA Research Network (SRN) to assess awareness of and compliance with the current NHSN requirements for device denominator data validation. **Results:** The survey was sent to 89 member institutions of the SRN from November 20, 2018, to December 12, 2018. The response rate was 35.7%, and 90% of respondents are currently using an electronic system for device denominator count reporting. All except 1 institution manually validated the data. Of the facilities that had completed validation, 31% used <90 days of manual data. Moreover, 82% of these facilities found a difference of <5% between the electronic data and manual data without a statistically significant difference between those with at least 90 days of validation data and those with <90 days. Also, 21% of facilities validated data based on a subset of units. **Conclusions:** Although most respondents to the survey validate electronically collected device denominator data in accordance with NHSN’s requirements, nearly one-third reported using shorter validation periods than NHSN requires.

However, shorter periods were not associated with worse concordance. The NHSN should evaluate whether the burden of a 3-month validation period is justified.

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Predicting Community-Onset Candidemia in an Academic Medical Center Using Machine Learning

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Background: Candidemia is a leading cause of bloodstream infections (BSIs), and community-onset candidemia is being recognized as a public health problem. In the era of electronic health records (EHRs), we can use machine learning to detect patterns in patient data that may predict infections. **Objective:** We aimed to predict community-onset candidemia in patients admitted to the University of Iowa Hospital & Clinics (UIHC) using machine-learning algorithms. **Methods:** We retrospectively reviewed data for patients admitted to UIHC during 2015–2018. All adult inpatients who had a requested blood culture were included. Candidemia was defined as a blood culture positive for *Candida* within 48 hours after admission. Variables of interest were extracted from the EHR: age, sex, body mass index, and month of admission. We also included comorbidities upon admission defined by the *International Classification of Diseases, 10th Revision, Clinical Modification* (ICD-10-CM): cardiovascular

diseases, neurological disorders, chronic pulmonary disease, dementia, rheumatoid disease, peptic ulcer disease, liver disease, diabetes mellitus, hypothyroidism, renal failure, coagulopathy, obesity, weight loss, fluid and electrolyte disorders, anemia, alcohol abuse, drug abuse, psychiatric diseases, malignancy, and HIV/AIDS. We calculated Charlson and Elixhauser scores based on ICD-10-CM codes. We also included prehospitalization conditions (90 days before admission): *Candida*-positive cultures from sites other than blood, antibiotics/antifungals, hemodialysis, central lines, corticosteroids, surgeries, and intensive care unit (ICU) admissions. Mode and median imputation were used for missing information. Random forests with resampled training sets were used for prediction, and results were evaluated using 10-fold cross validation. **Results:** In total, 30,528 adult admissions were extracted; 73 admissions had an episode of candidemia (<1%). Median admission age was 61 years, and nearly half of admissions were female patients (44.7%). Mean BMI was 27.67. The most admissions occurred during the months of March, August, and November. The 3 most common ICD-10-CM codes were diabetes mellitus, hypertension, and cancer. Median Charlson and Elixhauser scores were 1 and 2, respectively. The model used 103 variables. The 3 most predictive variables were Elixhauser score on admission, and characteristics in the 90 days prior to admission were *Candida* from sites other than blood, use of a central line, and recent use of antibiotics/antifungals. The model's area under the receiver operating characteristic curve was 0.72. **Conclusions:** Preadmission patient characteristics predicted community-onset candidemia. Machine-learning models may help detect patients eligible for screening for candidemia and prompt empiric antifungal therapy in high-risk patients in the first 48 hours of their admission.

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Prediction of Surgical Risk in General Surgeries: Process Optimization Through Support Vector Machine (SVM) Algorithm

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Background: In 5 hospitals in Belo Horizonte (population, 3 million) between July 2016 and June 2018, a survey was performed regarding surgical site infection (SSI). We statistically evaluated

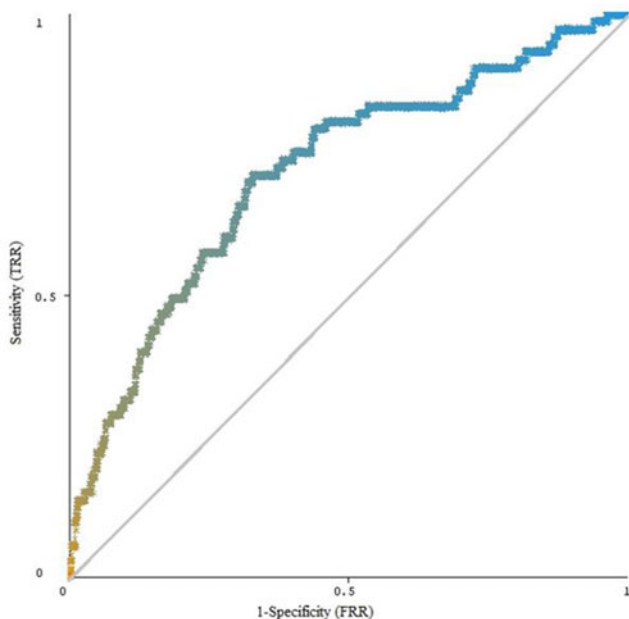


Figure 1: ROC curve

Fig. 1.