duodenoscopes (10%) are not adequately clean. Figure 2 shows a box-plot analysis of the data set by endoscope type and by site. There is significant ($P < .005$) site-to-site variability for all endoscope types as demonstrated by variation in mean values, box size, and many outliers. **Conclusions:** This study highlights the importance of using a quantitative cleaning verification method to better understand process capability and to provide more robust quality assurance for manual cleaning. Significant differences were detected in the level of cleanliness between upper GI scopes and lower GI scopes and bronchoscopes. When compared to a literature-supported level for adequate cleanliness, upper GI scopes exhibited failure rates in excess of 10%. Furthermore, significant site-to-site variability occurred, and many outliers fell well beyond the normal process envelope, representing significant cleaning lapses. Root causes to these concerning findings could range from inadequate execution of the cleaning protocol, to device design, to age and existing damage that could prevent achieving adequate cleaning and possibly impair the effectiveness of HLD.

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**Disclosures:** Marco Bommarito, 3M (salary)

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**Presentation Type:**

Distinguished Oral

**Mining Camera Traces to Estimate Interactions Between Healthcare Workers and Patients**

D. M. Hasibul Hasan, The University of Iowa; Philip Polgreen, University of Iowa; Alberto Segre, Department of Computer Science, University of Iowa; Jacob Simmering, The University of Iowa; Sriram Pemmaraju, University of Iowa

**Background:** Simulations based on models of healthcare worker (HCW) mobility and contact patterns with patients provide a key tool for understanding spread of healthcare-acquired infections (HAIs). However, simulations suffer from lack of accurate model parameters. This research uses Microsoft Kinect cameras placed in a patient room in the medical intensive care unit (MICU) at the University of Iowa Hospitals and Clinics (UIHC) to obtain reliable distributions of HCW visit length and time spent by HCWs near a patient. These data can inform modeling efforts for understanding HAI spread. **Methods:** Three Kinect cameras (left, right, and door cameras) were placed in a patient room to track the human body (ie, left/right hands and head) at 30 frames per second. The results reported here are based on 7 randomly selected days from a total of 308 observation days. Each tracked body may have multiple raw segments over the 2 camera regions, which we “stitch” up by matching features (eg, direction, velocity, etc), to obtain complete trajectories. Due to camera noise, in a substantial fraction of the frames bodies display unnatural characteristics including frequent and rapid directional and velocity change. We use unsupervised learning techniques to identify such “ghost” frames and we remove from our analysis bodies that have 20% or more “ghost” frames. **Results:** The heat map of hand positions (Fig. 1) shows that high-frequency locations are clustered around the bed and more to the patient’s right in accordance with the general medical practice of performing patient exams from their right. HCW visit frequency per hour (mean, 6.952; SD, 2.855) has 2 peaks, 1 during morning shift and 1 during the afternoon shift, with a distinct decrease after midnight. Figure 2 shows visit length (in minutes) distribution (mean, 1.570; SD, 2.679) being dominated by “check in visits” of <30 seconds. HCWs do not spend much time at touching distance from patients during short-length visits, and the fraction of time spent near the patient’s bed seems to increase with visit length up to a point. **Conclusions:** Using fine-grained data, this research extracts distributions of these critical parameters of HCW–patient interactions: (1) HCW visit length, (2) HCW visit frequency as a function of time of day, and (3) time spent by HCW within touching distance of patient as a function of visit length. To the best of our knowledge, we provide the first reliable estimates of these parameters.

**Funding:** None

**Disclosures:** None

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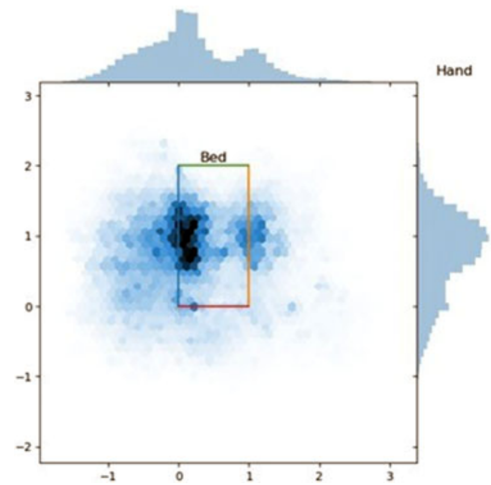


**Fig. 1.**

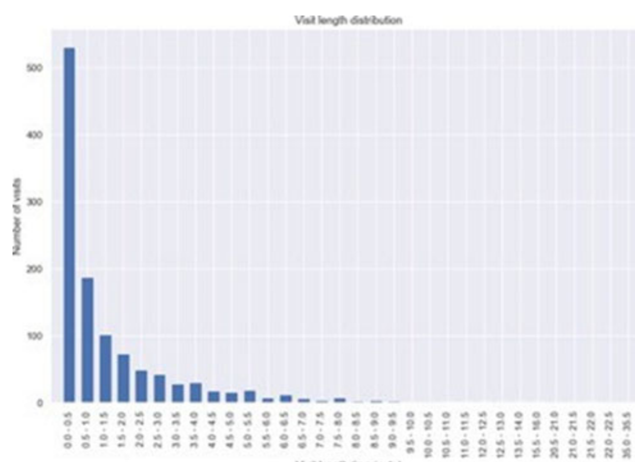


**Fig. 2.**

**Presentation Type:**

Distinguished Oral

**Novel Methodology to Measure Preprocedure Antimicrobial Prophylaxis: Integrating Text Mining With Structured Data**

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Table. Iterative Performance of Antimicrobial Prophylaxis Identification Algorithm in Development Stage with Gold Standard CART-EP Program Data (Manual Review; n=2,102 procedures in 38 facilities) *

| Data Elements in Algorithm | CART-EP-reviewed cardiac device procedures (n=2,102) | PPV (True flagged 'yes abx'/All flagged 'yes abx') | NPV (True flagged 'no abx'/All flagged 'no abx') | Sensitivity (All flagged 'yes abx'/Total 'yes abx' n=2,056) | Specificity (All flagged 'no abx'/Total 'no abx', n=46) |
|---|---|---|---|---|---|
| Manual review | 2,056 (97.8%) | -- | -- | -- | -- |
| Text note searches | 1,954 (93.0%) | 1,930/1,954 (98.8%) | 22/148 (14.9%) | 1,930 (93.9%) | 22 (47.8%) |
| Orders | 1,899 (90.3%) | 1,883/1,889 (99.2%) | 30/203 (14.8%) | 1,883 (91.6%) | 30 (65.3%) |
| Administration | 150 (7.14%) | 150/150 (100%) | 46/1952 (2.36%) | 150 (7.30%) | 46 (100%) |
| Text note searches + Orders | 2,048 (97.4%) | 2,019/2,048 (98.6%) | 17/54 (31.5%) | 2,019 (98.2%) | 17 (37.0%) |
| Text note searches + Administration | 1,955 (93.0%) | 1,931/1,955 (98.8%) | 22/147 (15.0%) | 1,931 (93.9%) | 22 (47.8%) |
| Orders + Administration | 1,901 (90.4%) | 1,885/1,901 (91.7%) | 30/201 (14.9%) | 1,885 (91.7%) | 30 (65.2%) |
| Text note searches + Orders + Administration | 2,048 (97.4%) | 2,019/2,048 (98.6%) | 17/54 (31.5%) | 2,019 (98.2%) | 17 (37.0%) |
| **Round 2 Changes:** | | | | | |
| Text note searches - Exclude oral medications | 1,950 (92.8%) | 1,928/1,950 (98.9%) | 24/152 (15.8%) | 1,928 (93.8%) | 24 (52.2%) |
| Limit list to common prophylaxis medications | 2,044 (97.2%) | 2,017/2,044 (98.7%) | 19/58 (32.8%) | 2,017 (98.1%) | 19 (41.3%) |
| Exclude notes from the day of the procedure | 823 (39.1%) | 823/825 (99.8%) | 44/1,277 (2.09%) | 823 (40.0%) | 44 (95.7%) |
| Include term "prophylaxis" in text searches | 2,048 (97.4%) | 2,019/2,048 (98.6%) | 17/54 (31.5%) | 2,019 (98.2%) | 17 (37.0%) |

* CART-EP Program data included 2,102 cardiac device procedures with manually collected data on antimicrobial prophylaxis; of these, 2,056 cases (97.8%) received antimicrobials prior to incision. Shaded cell indicates the final algorithm.

Abx=antimicrobial; PPV=positive predictive value; NPV=negative predictive value

System; Kelly Stolzmann, VA Boston CHOIR; Emily Kalver, VA Boston CHOIR; Marlena Shin, VA Boston CHOIR; Marin Schweizer, University of Iowa; Archana Asundi, Boston University Medical Center; Payal Mehta, VA Boston Healthcare System; Maggie Stanislawski, University of Colorado School of Medicine; Westyn Branch-Elliman, VA Boston Healthcare System

**Background:** Antimicrobial prophylaxis is an evidence-proven strategy for reducing procedure-related infections; however, measuring this key quality metric typically requires manual review, due to the way antimicrobial prophylaxis is documented in the electronic medical record (EMR). Our objective was to combine structured and unstructured data from the Veterans' Health Administration (VA) EMR to create an electronic tool for measuring preincisional antimicrobial prophylaxis. We assessed this methodology in cardiac device implantation procedures. **Methods:** With clinician input and review of clinical guidelines, we developed a list of antimicrobial names recommended for the prevention of cardiac device infection. Next, we iteratively combined positive flags for an antimicrobial order or drug fill from structured data fields in the EMR and hits on text string searches of antimicrobial names documented in electronic clinical notes to optimize an algorithm to flag preincisional antimicrobial use with high sensitivity and specificity. We trained the algorithm using existing fiscal year (FY) 2008-15 data from the VA Clinical Assessment Reporting and Tracking-Electrophysiology (CART-EP), which contains manually determined information about antimicrobial prophylaxis. We then validated the performance of the final version of the algorithm using a national cohort of VA patients who underwent cardiac device procedures in FY 2016 or 2017. Discordant cases underwent expert manual review to identify reasons for algorithm misclassification and to identify potential future implementation barriers. **Results:** The CART-EP dataset included 2,102 procedures at 38 VA facilities with manually identified antimicrobial prophylaxis in 2,056 cases (97.8%). The final algorithm combining structured EMR fields and text-note search results flagged 2,048 of the CART-EP cases (97.4%). Algorithm validation identified antimicrobial prophylaxis in 16,334 of 19,212 cardiac device procedures (87.9%). Misclassifications occurred due to EMR documentation issues. **Conclusions:** We developed a methodology with high accuracy to measure guideline-concordant use of antimicrobial prophylaxis before cardiac device procedures using data fields present in modern EMRs that does not rely on manual review. In addition to broad applicability in the VA and other healthcare systems with EMRs, this method could be adapted for other procedural areas in which antimicrobial prophylaxis is recommended but comprehensive measurement has been limited to resource-intense manual review.

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**Disclosures:** None
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**Presentation Type:**
Distinguished Oral

**Patients Discharged From Hospitals Without a *Clostridioides difficile* Infection Increase the Risk of CDI in Family Members**

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**Background:** *Clostridioides difficile* infections (CDIs) present and are transmitted in both community and healthcare settings. Patients who become colonized or infected during hospitalization may be discharged into the community. Asymptomatic spread and/or community-based transmission have also been posited as alternative sources for healthcare-onset CDI cases. The objective of our study was to determine whether individuals are at greater risk for developing a CDI if they have a family member that spent time hospitalized in the prior 90 days, even if the hospitalized family member had no prior diagnosis of CDI. **Methods:** We