were initiated. Statistical analysis was performed on the annual number of dispenses and opportunities with a mixed-effects Poisson regression with random effects for facility, unit and year and fixed effects for intervention type and unit type. Interactions were not included in the model based on interaction plots and significance tests. Poisson assumptions were verified with Pearson residual plots. **Results:** HH performance rates overall and compared to the baseline are shown in Table 2. More than 8 million opportunities were achieved in all 58 units combined. An intervention strategy with multiple complementary components (ie, clinical support provided by the AHHMS vendor plus hospital-initiated unit level interventions) yielded significantly better HH performance than all other categories (>20% increase, $P < .00001$). Somewhat surprisingly, vendor clinical support or hospital-initiated, unit-level interventions alone with the AHHMS yielded a slight decrease in HH performance relative to AHHMS only ($P < .00001$). **Conclusions:** AHHMS is a useful tool in understanding HH performance and identifying unit-based initiatives that need attention. Implementation of an AHHMS by itself or with limited complementary behavior-change strategies does not drive improvement. Support provided by the vendor and hospital-initiated, complementary strategies were not sufficient additions to the AHHMS individually, but in combination they resulted in the greatest improvements in HH performance. These findings illustrate the value of a partnership between the hospital and the AHHMS vendor.

Presentation Type:
Poster Presentation

Using Machine Learning to Detect Hospital-Specific Risk Factors of Surgical Site Infections

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Background: Identification of healthcare-associated infections (HAIs) is just a first step in the surveillance of HAIs. The other part is the analysis and interpretation of collected data, which should help to set up effective preventive measures targeted where they are needed the most. General risk factors of HAIs are mostly well known, but how do the environment and processes of each hospital affect risks of HAI? Can advanced methods of data analytics reveal hidden hospital-specific risk factors of surgical site infections (SSIs)? **Methods:** We analyzed data from electronic health records stored in the clinical information system of Hospital Jihlava, Czech Republic, with 650 beds and 7,500 surgeries performed annually. For each inpatient stay with a surgical procedure, we automatically observed almost 1,500 features that could lead to a higher incidence of SSIs. These features consist of patient demographic data, information from structured data (eg, patient diagnoses, departments, specific rooms, operating theaters, surgeons and other hospital staff participating in the surgery), and information extracted from clinical notes using natural language processing (eg, procedures, invasive devices, and comorbidities). We used a model based on survival analysis to reveal the risk factors that can increase the probability of SSI during the inpatient stay or outpatient care after discharge. **Results:** We automatically evaluated risk factors weekly for 4 months (July 2019–October 2019). We detected 16 distinct significant risk factors during this period—between 2 and 6 active risk factors each week. For example, patients visiting a specific department were up to 5 times more likely to develop an HAI than the rest of the patients ($P < .001$). Some of the risk factors revealed were significant only within a short time, and some of them occurred perpetually. When a feature became significant, it was considered an early warning of a problem that should be addressed by the infection prevention and control team. Trends in risk factors coefficients can also help in assessing the performance of the launched preventive measures. **Conclusions:** Advanced data analytics can effectively uncover hospital-specific risk factors affecting surgical site infections. Such systems can automatically deliver results that can be further explored and used as a basis for targeted preventive measures.

Presentation Type:
Poster Presentation

A Collaborative Public Health and Veterinary Facility Approach to an NDM-5 *Escherichia coli* Outbreak

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