~225,000 hospitalizations, 12,800 deaths, and ~\$1 billion in healthcare costs in the United States in 2017. The presence of the secreted toxins that cause the devastating symptoms of this gastrointestinal infection are diagnostic of C. difficile infection (CDI). However, the rapid testing methods currently used to detect CDI lack accuracy. Enzyme immunoassays are specific but lack sensitivity because they do not detect CDI patients that have low levels of the toxins. Nucleic acid amplification tests (NAATs) are sensitive, but they lack specificity because they detect patients colonized with C. difficile in the dormant spore form that does not produce the toxins. This insufficiency has resulted in the adoption of complex multitest algorithms for C. difficile diagnosis. We present results for a new toxin test that demonstrates both high clinical sensitivity and clinical specificity for *C. difficile* toxin B on a fully automated benchtop platform. Methods: The detection technology uses nonmagnified digital imaging to count single toxin molecules that tether together target-specific magnetic and fluorescent particles. The 30-minute method includes the use of a dye cushion to eliminate wash steps and the need for time-consuming specimen preparation steps. We determined analytical performance characteristics of the test using negative clinical stool samples spiked with purified toxin. To assess clinical performance, we tested 785 stool samples from 5 clinical sites and compared the results with the cellular cytotoxicity neutralization assay (CCNA). Results: The test's limit of detection for toxin B was 60 pg/mL. A comparison of the new test to the CCNA reference method gave 98% positive percentage agreement (83 of 85 samples) and 95% negative percentage agreement (667 of 700 samples). Conclusions: The new method demonstrated 96% accuracy compared to the gold standard for C. difficile toxin tests. The results also demonstrate an analytical sensitivity (limit of detection, 60 pg/mL). Thus, the test has the potential to detect CDI patients missed by enzyme immunoassay (EIA) tests due to their low analytical sensitivity. Because the test detects toxins directly, it is expected to have a lower false-positive rate than NAAT methods, which detect patients colonized with the non-toxin-producing spore form. A single accurate test for toxin-producing *C. difficile* could eliminate the need for multitest algorithms.

Funding: First Light Diagnostics, Inc., provided support for this study.

**Disclosures:** Donald Straus reports that he is the founder and chief scientific officer of First Light Diagnostics (FLDx) with salary and ownership interest in the form of stocks, stock options, and warrants. Adam Williams reports salary from First Light Diagnostics. Doi:10.1017/ice.2020.1121

## **Presentation Type:**

Poster Presentation

The Effect of Automated Hand Hygiene Monitoring Systems and Other Complementary Behavior-Change Strategies on

James Arbogast, GOJO Industries, Inc.; Lori Moore, GOJO Industries, Inc.; Megan DiGiorgio, GOJO Industries, Inc.; John Boyce, J.M. Boyce Consulting, LLC; Albert Parker, Center for Biofilm Engineering, Department of Mathematical Sciences Montana State University

Background: Technology and interest for use of automated hand hygiene monitoring systems (AHHMS) as a tool to help improve healthcare personnel hand hygiene has been advancing for the last decade. Emerging evidence indicates that the use of AHHMS plus complementary strategies improves hand hygiene (HH) performance rates and outcomes (eg, healthcare-associated infections). The WHO HH guideline "Multimodal Strategy" teaches the importance of multiple components as necessary to build and sustain HH compliance. Few published data compare the impact of different complementary behavioral strategies in combination with AHHMS on results. Methods: We utilized data from 1 AHHMS that records alcohol-based hand rub and soap dispensing and room entries and exits to provide group HH performance rates. Data were collected from 58 units in 10 hospitals in North America from July 2014 through August 2019. Hospitals were stratified into 4 categories based on their approach to hospital-initiated unit-level interventions and AHHMS vendor support (Table 1). Baseline data were defined for each unit as the initial 1-2 months of execution, before complementary strategies

Table 1.

Table 1: Summary of the Categories of Complementary Behavior Change Strategies in Addition to Automated Hand Hygiene Monitoring System (AHHMS)

Complimentary Behavior Change Strategies	Category Coding
Vendor-provided clinician support + hospital-initiated unit-level interventions	Vendor + Hospital
Vendor-provided clinician support with No hospital-initiated unit-level interventions	Vendor Only
Hospital-initiated unit-level interventions with No vendor support	Hospital Only
No vendor support + No hospital or unit-level interventions	AHHMS Only

Table 2.

Table 2: Hand Hygiene (HH)/Performance Data Sum by Complimentary Strategy

7.0	# Unit Months	# of Units	# of HH	#of HH	Median HH	HH % Change
Behavioral			Events	Opportunities	Performance	vs. AHHMS Only
Intervention					Rate [95% CI]	[95% CI]
Categories						
Vendor +	1,469	43	76,033,317	148,768,145	41.4%	+20.8%
Hospital					[37.0%, 46.4%]	[20.5%, 30.0%]
Vendor Only	72	6	2,320,736	8,786,285	33.3%	-2.9%
					[29.7%, 37.3%]	[-3.4%, -2.5%]
Hospital Only	384	8	11,755,028	37,485,325	32.3%	-5.8%
					[28.9%, 36.2%]	[-6.2%, -5.4%]
AHHMS	159	57	9,079,929	27,613,157	34.3%	Not Applicable
Only					[30.6%, 38.4%]	

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

**Funding:** GOJO Industries, Inc., provided support for this study. **Disclosures:** James W. Arbogast, Lori D. Moore and Megan DiGiorgio report salary from GOJO Industries.

Doi:10.1017/ice.2020.1122

## **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.

Funding: Datlowe provided support for this study.

**Disclosures:** Jakub Kozák reports salary from and ownership of Datlowe.

Doi:10.1017/ice.2020.1123

## **Presentation Type:**

Poster Presentation

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

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