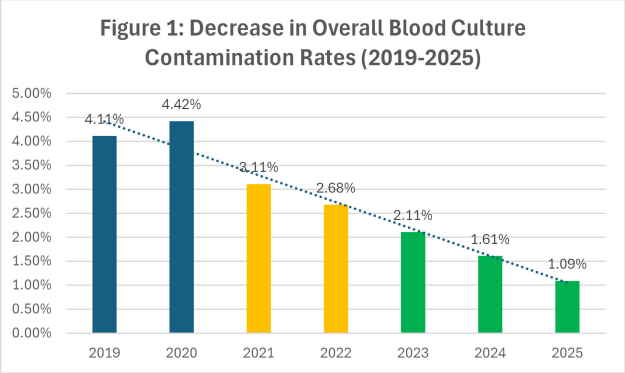


define <3% contamination as acceptable, yet emerging evidence supports a more ambitious goal of ?1%, particularly in high-risk populations such as patients with sepsis. Methods Using a sequential practice change across three time periods: (1) no blood culture diversion device (2019–2020), (2) implementation of manual blood diversion device (BDD) #1 (2021–2022), and (3) automatic BDD#2 (2023–present), we have achieved a 74% reduction in BCC (Figure 1). In this project, we further evaluated the impact of this overall reduction on patients admitted with suspected or confirmed sepsis. Results Data were extracted for adult patients admitted to the hospital who had a final discharge diagnosis of sepsis, regardless of their initial admission diagnosis. A total of 154 blood cultures were analyzed across the three time periods. During period 1 (2019 & 2020), 6/62 cultures were contaminated (9.7%). After implementation of manual BDD#1 (11/17/2021-2022), BCC decreased to 2/30 cultures (6.7%). After transition to automatic BDD#2 (1/20/2023-present), BCC further declined to 3/62 cultures (4.8%). One-way analysis of variance (ANOVA) demonstrated a statistically significant difference in BCC rates across the time periods, with post hoc comparisons showing a significantly lower contamination rate when using BDD#2 as compared with both no BDD and manual BDD#1. Additionally, manual BDD#1 was used in 48% (30/62) of the blood culture collections versus to 78% for automatic BDD#2, with staff feedback indicating greater ease of use with the automatic BDD#2 system. Conclusion Adoption of BDD was associated with a 50% (9.7-4.8%) reduction in BCC, with the lowest rates following implementation of automatic BDD#2. Compliance with BDD use was also highest with automatic BDD#2, and staff reported greater ease of use. These findings underscore the importance of optimizing BCC practices as a key component of sepsis management, antimicrobial stewardship, and patient safety efforts. Additional research is needed to identify strategies to further reduce BCC in sepsis patients, with particular attention to BDD usability, workflow integration, and process adherence during real-world use.

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Presentation Type:
Poster Presentation
Subject Category: Technology
Development of a shared patient registry for measles exposure management amongst multiple stakeholder groups‡

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Background: We had a large-scale measles exposure event affecting 626 patients. Management of exposed patients was urgent, involving quarantine, post-exposure prophylaxis (PEP), and symptom monitoring on a case-by-case basis. Cases were initially tracked and managed using a combination of multiple spreadsheets amongst stakeholders as well as lists within the electronic health record (EHR). Using shared spreadsheets and lists created significant challenges with maintaining and editing multiple copies and updating workbooks simultaneously. **Methods:** Infection Prevention and Control (IPAC) worked with primary care personnel and EHR developers to create a shared registry that would prioritize communication and follow-up for exposed patients based on age and immunity. Patients are initially added to the shared registry within the EHR by reviewing non-registry reports and tagging patients, identified using exposure timeframes that overlapped with the index measles cases, in a manner that transferred them to the shared registry. From this registry, measles, mumps, and rubella vaccine status can be confirmed, immune status can be identified, and criteria for PEP assigned. High-risk patients are then contacted with recommendations from IPAC and primary care. Communication and follow-up are tracked directly within the shared registry to ensure appropriate patient management. The exposure management registry is further leveraged throughout the measles outbreak timeframe by allowing real-time monitoring of patients that require additional precautions or guidance related to their exposure. **Result:** The shared registry enhanced documentation accuracy and transparency between stakeholders. It led to availability of real-time status of exposed patients for the duration of the measles outbreak timeframe. Overall, the registry enabled time-sensitive patient communication to all exposed patients and rapid identification of those who needed PEP. Communication could happen rapidly and seamlessly between care teams within the organization, and the necessary information could be shared quickly with public health authorities as required. **Conclusion:** Large scale exposures are a challenge to manage and ensure appropriate action and communication occurs. Errors can be prevented by having a single shared exposure management registry. A registry enables care teams to quickly identify and prioritize patients for measles follow-up, communication, PEP, and ongoing management across outbreak timeframes. This process reduces both time and operational burdens of exposure follow-up tracking outside of the EHR.

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Presentation Type:
Poster Presentation
Subject Category: Technology
A Predictive Modeling Approach to Reduce Pediatric Central Line-Associated Bloodstream Infections‡

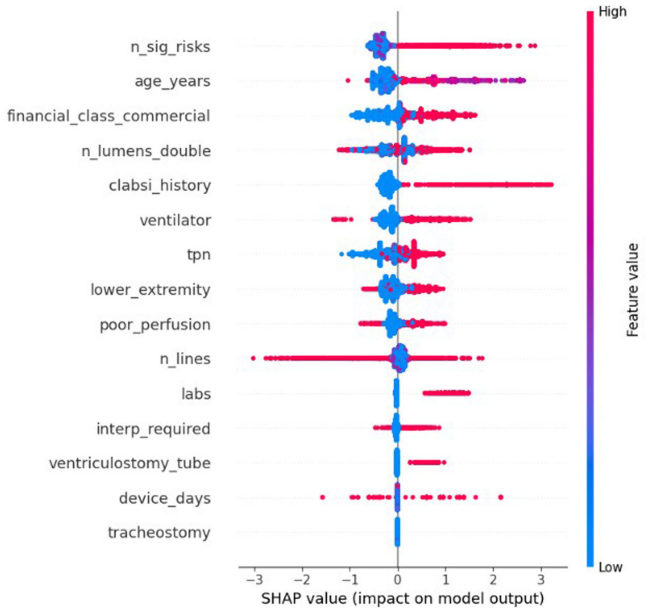
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Background: Central line-associated bloodstream infection (CLABSI) represents the most common and costly device-associated hospital-acquired infection in children. While prevention bundles are effective when reliably implemented, pediatric-specific risks often require strategies beyond standard bundles. Existing CLABSI risk models are insufficient for pediatric patients, remaining static during their hospital stay despite changing clinical conditions. Moreover, previously reported dashboards and predictive models generally do not incorporate data science principles to provide a daily prediction score, and they often exclude demographic factors beyond age and sex. The purpose of developing the CLABSI risk model was to leverage technology-driven strategies for identifying, intervening, and escalating care for high-risk pediatric patients in real time, thereby decreasing infection risk. **Methods:** Quality Improvement, Data Intelligence, and the interdisciplinary clinical team partnered to develop an evidence-based predictive model tailored to institutional risk factors. Using evidence and clinical expertise, an affinity diagram was created. Data from 61,068 inpatient central line days (January 2022- July 2024), sourced from electronic health records (EHR) and clinical surveillance software, formed the dataset. CLABSI was identified using NHSN surveillance definition. Patient risk factors from the infection date plus two days prior were evaluated.

‡The abstract titles in this supplement have been corrected since original publication. A notice detailing the changes has been published at https://doi.org/10.1017/ash.2026.10802.

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Risk Factor	Tunneled Lines Model	Nontunneled Lines Model
Diaphoresis	X	X
Drainage	X	
Ecchymosis	X	X
Edema	X	X
Erythema	X	X
Leak		X
Nonocclusive dressing		X
Not flushing	X	X
Not intact	X	X
Phlebitis		X
Pulled	X	
Soiled dressing	X	X



Exploratory data analysis was completed using RStudio integrated development environment to inform model development. Separate models were created for nontunneled lines and tunneled lines. Prediction models were developed using Python coding language and Databricks data intelligence platform. Under-sampling was used to account for uneven distribution between CLABSI and non-CLABSI cases. Logistic regression, random forest, and XGBoost models were created. Candidate models were compared using area under the curve (AUC), sensitivity, and specificity. **Result:** Using the XGBoost model for nontunneled line, the test AUC was 0.831, demonstrating strong discriminative power. This model achieved a sensitivity of 0.828, indicating its ability to correctly identify a high proportion of actual CLABSI cases, and a specificity of 0.751, reflecting its capacity to correctly identify non-CLABSI cases. Similarly, the tunneled line XGBoost model yielded an AUC of 0.845, showcasing excellent predictive performance. Its sensitivity was 0.833 and specificity was 0.668. In both models, the number of modifiable risks was the most significant factor (Tables 1-3). **Conclusion:** The CLABSI prediction model enables real-time identification and intervention to support proactive prevention, leveraging these performance characteristics to improve patient care. While predictive modeling has limitations due to EHR documentation, clinician expertise and frontline team engagement remain essential for deploying resources to highest risk patients.

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Fig 1

IP Validation Round	Intent (N = 0, Y = 5)	Relevance (N = 0, Y = 5)	Accuracy (N = 0, Y = 5)	Completeness (1-5)	Consistency (1-5)	Overall
1	5.0 (100%)	4.2 (84%)	3.2 (64%)	3.8 (76%)	4.5 (90%)	84%
2	5.0 (100%)	4.5 (90%)	3.1 (62%)	3.6 (72%)	4.4 (88%)	82%

Fig 2

IP Validation Round	Intent (1-4)	Accuracy (1-4)	Completeness (1-4)	The response helped me achieve my intended goal (1-4)	This content is ready to be deployed to end users (1-4)	Overall
3	3.9 (99%)	3.8 (94%)	3.7 (93%)	3.7 (92%)	3.6 (89%)	93%

Fig 3

Nurse Manager Validation Round	Intent (1-5)	Trust Accuracy of Response (1-4)	Completeness (1-5)	The response helped me achieve my intended goal (1-5)	Ease of Use (1-4)	Overall
1	4.7 (94%)	3.2 (79%)	4.5 (91%)	4.3 (86%)	3.8 (95%)	89%

Fig 4

Queries	Optimal	Suboptimal/ No Harm	Suboptimal/ Possible Harm
29	20	1	8

Presentation Type:
Poster Presentation
Subject Category: Technology

Validation of an Internal Infection Control Chatbot‡

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Background: Effective infection prevention and control is integral to the delivery of safe patient care, and with ever increasing demands on their attention, systems to help navigate policy-based guidance can support infection preventionists (IPs) and their healthcare colleagues. Here we present the validation process and results for an internal infection control chatbot. **Methods:** Eleven frequently asked questions were selected to evaluate the performance of ChatUCM, an AI-powered chatbot. Each question was posed five times and response quality was scored by intent recognition, relevance, accuracy, completeness, and consistency. A category pass threshold was set at 75%. IP feedback was incorporated in a ChatUCM update and response quality was scored again. Reference document edits and real-time prompt modifications were made based on post-update scores. A final round of scoring was performed using similar validation metrics. Two IPs scored a subset of five out of the eleven frequently asked questions to assess interrater reliability. Six nursing managers were invited to ask ChatUCM any questions and score its responses by intent recognition, their ability to trust response accuracy, whether their question was fully answered, the achievement of intended goals, and ease of use. 29 questions were submitted. An IP reviewer also scored these ChatUCM responses as optimal, suboptimal/ no harm, and suboptimal/ possible harm. **Results:** The impact of the update on scores was variable. ChatUCM performed well on the same 7 out of 11 questions before and after validation round 1 (Fig. 1). After the final round of retraining, ChatUCM passed all categories with high interrater reliability for our frequently asked questions (Fig. 2). Response quality was less predictable outside of these eleven questions (Fig 3, Fig 4). To ensure its safe use, multiple safety checks were created, including disclaimer language, citation links, education, and a query report to facilitate audits. We encountered multiple surprises while validating ChatUCM. The first update resulted in significant improvements, such as the ability to digest data in table and flow

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