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Abstract

Purpose: The Connected Emergency Care (CEC) Patient Safety Learning Lab aimed to mitigate health and financial harms arising from fragmented emergency care systems. The lab focused on improving diagnostic accuracy, antibiotic specificity, and transition of care outcomes for respiratory infections in emergency departments (EDs).

Scope: Under the hypothesis that electronic health record (EHR) data can forge new clinician-patient connections to enhance care, the project took place in Johns Hopkins Health System's EDs. It addressed the challenges of ED care, where decision-making demands are high amidst information scarcity and high patient turnover.

Methods: Utilizing a five-phase innovation cycle and Agile methodology, the multidisciplinary team developed a granular EHR-derived data repository, enabling quantitative analysis and identification of care gaps. Key activities included focus groups, task analysis, process mapping, and critical decision method interviews informed by naturalistic decision-making theory. Methods encompassed EHR data mining, machine learning, natural language processing, regression modeling, and user-centered design to develop EHR-embedded clinical decision support (CDS) tools.

Results: Broad problem analysis identified high-quality existing care and areas for improvement in infectious disease management. Notable projects included the development of the LOOP platform for post-encounter feedback, resulting in enhanced clinician engagement with patient outcomes. Interventions also led to significant reductions in inappropriate antibiotic prescribing, revealing racial and socioeconomic disparities in prescription practices. During the COVID-19 pandemic, the lab's infrastructure supported rapid policy development and implementation of ML models to guide patient disposition, demonstrating the value of data science in emergency care.

Key Words: emergency care, respiratory infection, clinical decision support, patient safety, systems engineering.

Purpose

The objective of the **Connected Emergency Care (CEC) Patient Safety Learning Lab** was to reduce health and financial harms caused by a fragmented emergency care system. Within this system, lack of longitudinal relationships between clinicians and patients drives care without context. Practice-based learning and outcomes-based decision making are limited by an absence of post-encounter feedback. These disconnects are compounded in the emergency department (ED) by a hazardous decision-making environment fraught with time pressure and excessive cognitive loading. Electronic health records (EHRs) and health information technology (HIT) infrastructures hold potential for improvement of these conditions. We sought to reduce health and financial harms caused by suboptimal diagnosis, treatment, and disposition decisions using advanced data science methods and EHR-integrated clinical decision support (CDS). Using this approach, we aimed to establish a connected (closed-loop) emergency care system.
Our overarching aims were to (1) optimize **diagnostic performance**, (2) increase the **specificity of antibiotic treatment**, and (3) improve **transition of care outcomes** for patients with or suspected of having respiratory infections. Clinical decision making in this population is complicated by nonspecific and overlapping disease presentations, and diagnosis, treatment, and disposition decisions are highly variable. Our aims targeted these three decision points in the care continuum to maximize impact on health and cost outcomes.

Scope

Background and Context: The ED is a unique clinical environment where decision-making demands are high and information availability is low. In the United States, ED visits nationwide have climbed to over 140 million per year. Emergency clinicians now perform initial evaluations, stabilize, and set care trajectories for most hospitalized patients. They provide definitive care for the many more discharged into the community after ED care is complete. They do this under very challenging conditions. In most cases, they have never met the patients they are caring for and they very rarely receive any information about patients' care trajectories and outcomes after leaving the ED. Widespread adoption of the EHR has generated potential to reduce risk through personalized and data-driven decision support, but, in its current state (optimized for billing), the EHR drives additional disconnect. Important clinical information is often buried deep in the EHR, essentially inaccessible during the ED encounter. EM has historically been a bedside specialty, yet ED clinicians now spend more than half their time documenting in the EHR. ED overcrowding is now commonplace across the country, driving excessive waiting and further increasing risk. Overcrowding is a threat to patient safety associated with high rates of error, avoidable clinical deterioration, and excess morbidity and mortality across many conditions. A growing proportion of low-acuity patients present additional challenge to EDs, as high-stakes patients must be managed alongside those with less pressing pathology in a culture with zero tolerance for mistakes.

We hypothesized that EHR data could be used to build new connections between clinicians and patients that improve care in this unique setting. Our aims were executed in parallel by taking a systems engineering approach to CDS development that connected ED clinicians to patients' **pre-encounter** context, **post-encounter** outcomes, and **intra-encounter** current and projected state. Advanced data science, user-centered design, human factors engineering, decision sciences, and principles of health informatics were employed during electronic health record (EHR)-embedded CDS development and in the products that result. We sought to design tools with the ability to adapt to the uniqueness of diverse ED settings while having capacity to scale.
Setting and Participants: This project was led by a team of investigators within the Department of Emergency Medicine at the Johns Hopkins School of Medicine but was completed through collaboration between the Johns Hopkins School of Medicine, Johns Hopkins Whiting School of Engineering (Malone Center for Engineering in Healthcare), the Johns Hopkins-affiliated digital health startup company StoCastic, and the Center for Social Design within the Maryland Institute College of Art. Research was conducted in the EDs of five hospitals within the Johns Hopkins Health System: Johns Hopkins Hospital, Bayview Medical Center, Howard County Medical Center, Suburban Hospital, and Sibley Memorial Hospital.

Methods

Our multidisciplinary team employed five-phase innovation cycles and Agile methodology to drive work over the multi-year award period. Innovation cycles included (1) problem analysis, (2) solution design, (3) solution development, (4) implementation, and (5) evaluation. Time spent on each phase varied between individual projects.

Our first year was dedicated to broad problem analysis that determined our team's trajectory. During this period, our core team within the Center for Data Science in Emergency Medicine (CDEM) at Johns Hopkins School of Medicine constructed a highly granular EHR-derived data repository that facilitated in-depth quantitative analysis of current ED practice and allowed us to identify potential gaps in care that could be addressed using data-informed care. This data repository also enabled our team to respond rapidly to unanticipated events and to make important discoveries that guided clinical care regionally and nationally (see *Results* for further detail). We performed focus groups with primary CDS users and key stakeholders, including physicians (emergency, infectious disease, primary care, and internists), nurses, pharmacists, and administrators. We performed structured observations using task analysis methods and created process and value stream maps to better visualize work processes and understand interactions between system components. Finally, informed by all the activities above, we performed case-based critical decision method interviews that allowed our team to identify high-yield targets for data-informed CDS use. Interviews were anchored in naturalistic decision-making theory and focused on cases identified as aberrant using our EHR data repository and informed by CDS users and stakeholders described above.

Findings from this initial phase of our project led to the initiation and completion of numerous inter-related subprojects (described in *Results* below), each of which had a specific focus on diagnostic, treatment, and/or disposition decision making for infectious disease management in the ED. Subprojects performed with the aim of CDS tool development also followed five-phase innovation cycles, whereas those that aimed to generate knowledge or inform practice with empiric data followed a more traditional scientific approach. Methods used across subprojects included EHR data mining, machine learning, natural language processing, regression modeling, human factors engineering, and user-centered design.

Results

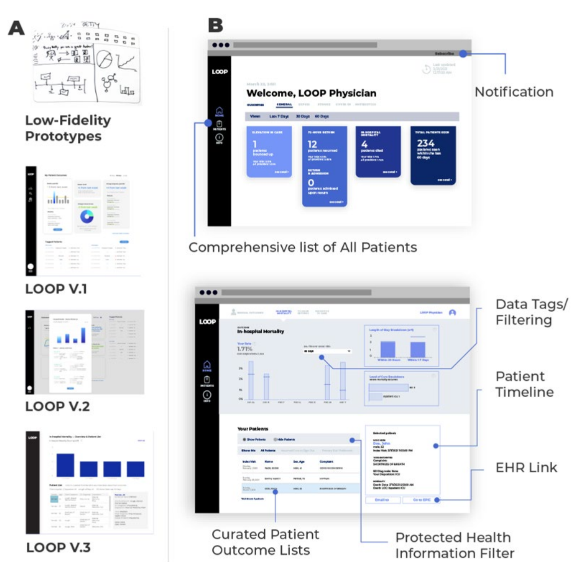
Our first year of broad problem analysis revealed that ED clinicians were already providing high-quality care for patients with infections. However, it also confirmed that opportunity existed to support and improve infectious disease management in the ED. Potential targets identified included provision of targeted decision support related to antibiotic treatment for infections and strengthening of connections among inpatient, outpatient, and ED treatment teams. Our most robust, and perhaps surprising, finding was that no mechanism existed to provide feedback on care provided in the ED. During our critical decision method interviews, we learned that less than 20% of ED clinicians were aware of adverse clinical events that occurred after their involvement in the patients' care ended. All interviewed indicated a desire for this feedback and identified it as critical to practice-based learning and improvement (PLBI). This finding informed our next project, which focused on provision of patient outcome information to enable PBLI.

LOOP: In collaboration with our partners at MICA, we created a patient outcomes feedback platform, named Linking Outcomes Of Patients (LOOP), tailored for emergency medicine (EM) clinicians. This initiative leveraged EHR data to provide clinicians with insights into both short-term and long-term outcomes of their patients. By addressing the feedback gap in episodic care environments, the project sought to enhance clinicians' ability to learn from patient outcomes, thus potentially improving patient care and safety. The study was conducted in three phases, employing a human-centered design (HCD) approach to ensure the developed platform would meet the needs and preferences of EM clinicians. A full description of this project is published in *JMIR Human Factors*.[1]

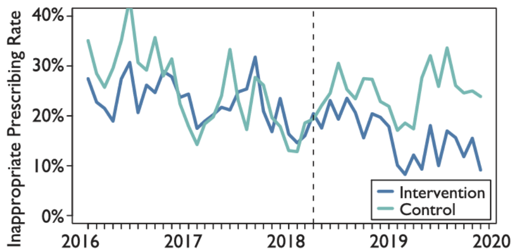
The first phase, Conceptual Development (corresponding to *problem analysis* and *solution design* above), involved engaging with EM clinicians and other stakeholders to identify their needs and preferences regarding patient outcome feedback. Through observations, semi-structured interviews, and surveys, a team of designers from MICA gathered in-depth insights into clinicians' experiences and challenges in obtaining patient outcome feedback. This resulted in the development of clinician "personas" and "design principles," which guided the subsequent development of the LOOP platform. The second phase, Technical Development, focused on the selection of patient outcomes for inclusion in LOOP based on clinician preferences and data feasibility. A data processing pipeline was developed to normalize and integrate EHR data, ensuring that patient encounters could be accurately attributed to individual clinicians. The LOOP digital platform was then developed in collaboration with EM clinicians to ensure its usability and relevance to their practice (see Figure below). The final phase, Usability Evaluation, involved a detailed assessment of the platform's usability and effectiveness. Twelve EM physicians interacted with LOOP for a minimum of 30 minutes, followed by surveys and interviews to assess the tool's usability, effectiveness, and potential for enhancing clinical practice. This phase aimed to evaluate the platform's impact on clinicians' confidence in and ease of obtaining patient outcome information as well as their likelihood of recommending the platform to colleagues.

This subproject uncovered significant themes of disconnection between clinicians and patients post-encounter, highlighting a need for more balanced and accessible feedback on patient outcomes. The development of the LOOP platform was driven by a focus on features such as comprehensive lists, EHR interoperability, and data tagging aimed at facilitating easy access and interpretation of patient outcome data for clinicians. The usability evaluation demonstrated that LOOP significantly improved clinicians' abilities to obtain and feel confident about patient outcome information. Notably, the platform was highly rated for its potential to enhance clinical decision making and practice-based learning, with a recommendation score of 9.5 out of 10 from participants. Feedback from this phase also provided valuable insights into areas for further refinement of LOOP, particularly regarding the optimization of data visualization and the integration of additional outcome metrics to enrich the feedback provided to clinicians. LOOP is currently used in clinical practice at Johns Hopkins and is enabling PBLI, informing quality improvements at the department level, and facilitating numerous other research projects, including those listed below.

ANTIBIOTIC PRESCRIBING AUDIT AND FEEDBACK PLATFORM**:** Based on findings described above and using infrastructure previously developed, we next aimed to reduce inappropriate antibiotic prescribing for acute respiratory infections (ARIs) using EHR data audit and peer comparison with behavioral feedback. We sought to leverage an automated algorithm to provide attending physicians with feedback on their prescribing patterns in comparison to their peers and incorporated this as a module within LOOP (described above).



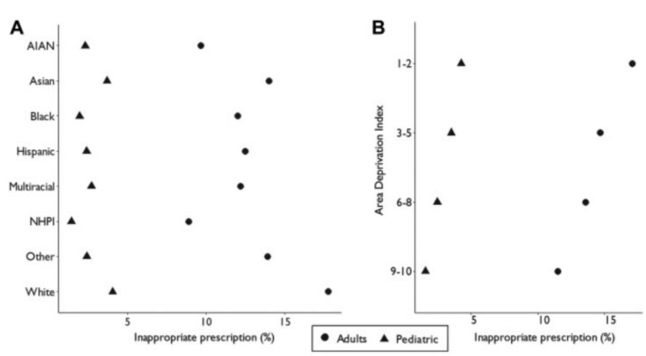
A controlled before-and-after study was conducted across five adult EDs within our health system, encompassing academic, teaching, and community hospitals. The intervention involved sending biannual emails to attending physicians at three EDs, informing them of their inappropriate ARI prescribing rate alongside a dashboard updated daily with peer performance for additional context. The study period was divided into pre-intervention and post-intervention phases, with two EDs serving as controls. Inappropriate ARI prescribing rates were calculated based on encounters deemed unnecessary for antibiotics, excluding hospitalizations and diagnoses potentially warranting antibiotics. The findings were published in *Antimicrobial Stewardship and Healthcare Epidemiology.*[2]



Out of 28,544 ARI encounters, the study found a significant decrease in inappropriate prescribing rates at intervention sites (from 22.0% to 15.2%) post-intervention, but rates at control sites remained stable (see figure above). The overall ARI prescribing rate also decreased in the intervention group (from 35.9% to 30.6%) but slightly increased in the control group (from 38.1% to 40.6%). Notably, the intervention led to decreases in prescribing across all diagnostic categories of ARI encounters in which antibiotics were deemed inappropriate. By providing attending physicians with regular feedback on their prescribing rates relative to their peers, the intervention prompted a significant change in behavior, contributing to the overall goal of reducing unnecessary antibiotic use and combating antibiotic resistance. This intervention, now facilitated by the LOOP platform, demonstrates a scalable and resource-efficient approach to improving antibiotic stewardship in acute care settings.

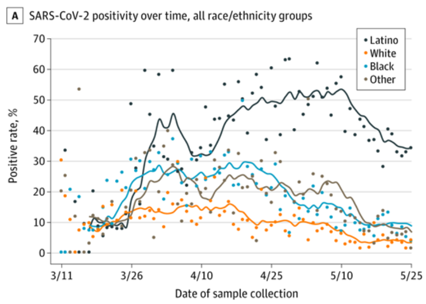
ANTIBIOTIC PRESCRIBING DISPARITIES**:** Using the tools described immediately above, we investigated the influence of race and socioeconomic status on inappropriate antibiotic prescribing for ARIs in ED. This subproject specifically focused on whether prescribing rates, guided by established guidelines indicating when antibiotics are unnecessary, varied among different racial and socioeconomic groups. We performed a retrospective cross-sectional analysis that covered adult and pediatric patient encounters from 2015 to 2023 at five hospitals. The study utilized multivariable regression to examine the association between patient demographics (race, ethnicity, area deprivation index) and the likelihood of receiving an inappropriate antibiotic prescription, controlling for variables such as age, sex, and comorbidities.

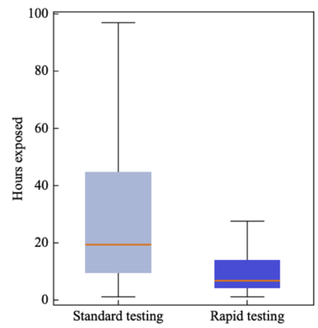
Out of 147,401 ED encounters analyzed, inappropriate antibiotic prescribing occurred in 7.6% of the cases. White patients were notably more likely to receive an inappropriate prescription compared to Black, Asian, and Hispanic patients, with adjusted analyses showing that White patients had a 1.32 times higher likelihood of receiving such prescriptions. Additionally, disparities were evident along socioeconomic lines, with patients from wealthier areas more likely to receive inappropriate antibiotics than those from areas with greater socioeconomic deprivation. As shown in the figure below, we found significant disparities in inappropriate antibiotic prescribing in EDs, with White patients and those from wealthier areas more likely to receive unnecessary antibiotics. These findings suggest underlying biases and systemic issues in healthcare delivery, emphasizing the need for targeted interventions to address these disparities and improve antibiotic stewardship. This study, published in *Annals of Emergency Medicine*,[3] further highlights the ongoing challenges and disparities within healthcare practices, particularly in the context of antibiotic prescribing.



The study also underscores the critical need for equitable healthcare practices that are devoid of racial and socioeconomic biases. These findings are informing additional research by our group and others.

DECISION SUPPORT DURING EARLY PHASES OF THE COVID-19 PANDEMIC: When COVID-19 emerged in 2020, our team was forced to shift focus but was well positioned to make important contributions in an uncertain time. Our project and associated data science assets, including our ED-focused EHR-derived data repository optimized for the study of respiratory infections, had matured to the point that we were able to meaningfully support institutional and regional decision making during the pandemic.





Very early in the pandemic, ED clinicians on our team anecdotally noted outsized impact of COVID-19 on our Latino population. In response, we conducted an analysis that leveraged EHR data from our ED data repository and outpatient clinics within the Johns Hopkins Health System to measure the relative frequency of SARS-CoV-2 infection across racialized and ethnic groups. Out of 37,727 patients tested, 6,162 (16.3%) were positive for SARS-CoV-2. As shown in the figure above left, the positivity rate among Latino patients was significantly higher (42.6%) compared to White patients (8.8%), Black patients (17.6%), and patients of other racial/ethnic backgrounds (17.2%). This study, published in *JAMA*[4], highlighted the need for targeted public health interventions to address the spread of SARS-CoV-2 in the Latino community and led to the creation of a program dedicated to COVID-related health in this community within the Baltimore-Washington, DC, metro area.

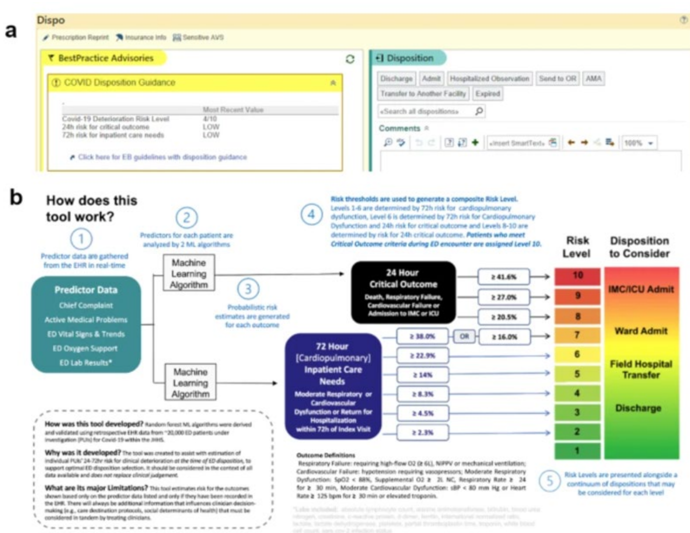
In the setting of critical personal protective equipment (PPE) shortages and a need to limit spread of SARS-CoV-2 in the hospital setting, we leveraged our EHR data infrastructure to inform policies that guided rapid diagnostic testing for SARS-CoV-2 at our institution. We undertook a cohort analysis to evaluate the impact of targeted rapid molecular testing for SARS-CoV-2 on healthcare-related exposure, resource conservation, and care capacity enhancement. We examined testing outcomes at three EDs within our health system between March and June 2020.

Rapid molecular testing was implemented in the ED alongside standard platform testing, with rapid tests prioritized for patients anticipated to require hospitalization or those unable to self-isolate. We found that, compared to standard testing, rapid testing significantly reduced the median time uninfected patients spent in isolation cohorts and exposed to COVID-19 by 65.6% (see figure above right). This reduction not only decreased potential healthcare-related exposure to SARS-CoV-2 for these patients but also resulted in significant resource savings and increased COVID-19 treatment capacity. Over the analysis period, we observed a total of 3028 bed-hours saved per week, translating to 7500 fewer patient interactions requiring personal protective equipment (PPE) and an estimated cost-saving of over $650,000 in non-reusable PPE alone. By effectively decreasing the time uninfected patients were treated alongside confirmed-positive patients, we conserved infection control resources, mitigated avoidable healthcare costs, and minimized the risk of nosocomial infection, underscoring the benefits of rapid testing beyond merely expedited diagnostic results. This study was published in the *Journal of Hospital Infection* and served as a model for use of limited rapid testing nationally.[5]

IMPROVING DISPOSITION DECISION MAKING FOR ED PATIENTS WITH RESPIRATORY INFECTION: Through a unique collaboration between our research team, health system leadership, and another research team funded by the Centers for Disease Control and Prevention, we rapidly developed, deployed, and studied an end-to-end CDS system to improve disposition decision making for patients with or suspected of having COVID-19. Our data architecture served as the backbone for this project and was used to develop machine learning (ML) models that estimated short-term risk of clinical deterioration in patients who had undergone diagnostic testing for COVID-19 or been placed in isolation for presumed COVID-19. Our goals were to refine emergency department (ED) admission decisions by differentiating patients who required hospital resources from those who could be safely discharged and identifying those at highest risk for critical care needs. Given the novelty and variability of COVID-19, these decisions were unusually challenging, and inpatient care resources were unusually restricted.

A retrospective cohort of 21,452 ED patients across five sites formed the basis for ML model derivation. We predicted the need for critical care resources within 24 hours and inpatient care resources within 72 hours post-ED visit. ML models were validated prospectively on 15,670 ED visits. As shown below, model outputs were translated into COVID-19 Deterioration Risk Levels, integrated within the EHR to aid clinicians in real-time decision making. Critical care and inpatient care needs within the stipulated time frames occurred in 10.7% and 22.5% of cases, respectively. The ML models demonstrated high performance, with areas under the curve (AUCs) ranging from 0.85 to 0.91 for critical care predictions and 0.80 to 0.90 for inpatient care predictions. Notably, after implementing the CDS, there was a reduction in mortality among high-risk patients, indicating the system's potential to significantly impact patient outcomes.

There were over a hundred reports of ML models intended to guide decision making during the COVID-19 pandemic, but our study (published in *npj Digital Medicine*) was one of very few to describe the implementation and evaluation of ML-driven decision support for COVID-19 in the real-world clinical environment.[6] The breadth and depth of this work would not have been possible without multidisciplinary collaboration and preliminary work performed under this AHRQ Patient Safety Learning Lab award. The EHR-integrated CDS system we developed was a significant advancement in the utilization of ML for real-time clinical decision support in the ED. Our team's experience and data infrastructure created during this project has propelled many other projects, including the derivation and validation of ML models to identify adult patients with influenza at increased risk for severe outcomes[7] and several ML models to guide ED care for pediatric patients (see *Abstracts and Presentations* below).



a Model-generated COVID-19 Deterioration Risk Levels were displayed in real-time for every patient with or under investigation for COVID-19 within the electronic health record (EHR). A screenshot of the emergency clinician disposition (Dispo) module is shown. **b** A hyperlink embedded within the Dispo module (bottom left of panel a) allowed emergency clinicians to access a more detailed explanation of model development and function within the EHR.

STRENGTHENING PRE-ENCOUNTER CONNECTIONS USING PRE-ARRIVAL ALERTS: Another subproject focused on the connection between emergency medical service (EMS) and the ED. EMS providers play an important role in the care of critically ill patients prior to their arrival in the ED (pre-encounter context). EMS and hospital system records do not share a common system, and there is often significant information loss at the point of transition between these teams. A potential mode for strengthening pre-encounter connection is through the pre-arrival relay of alerts from EMS to the ED. We conducted a retrospective cohort study to evaluate the impact of prehospital sepsis alerts on the timing of completing the Centers for Medicare and Medicaid Services (CMS) sepsis management bundle. We asked whether these alerts could decrease the time needed for blood culture collection, serum lactate collection, initiation of intravenous fluid administration, and initiation of broad-spectrum antibiotics.

Our study included 1491 patients transported by the Howard County Department of Fire and Rescue Services to HCGH between December 1, 2018, to December 1, 2019. We compared outcomes between septic patients who had a prehospital sepsis alert activated by EMS providers against those who did not. We found that median time to achieve all four studied CMS sepsis core measures was slightly shorter for patients with a prehospital sepsis alert than for those without (103 min vs. 106.5 min), although this difference was not statistically significant (p-value 0.105). Individual measures such as serum lactate collection, blood culture collection, and intravenous fluid administration showed significantly shorter completion times in the alert group; antibiotic administration time did not significantly differ between groups. There were no changes in mortality. This study, published in the *American Journal of Emergency Medicine*,[8] suggests that, although prehospital alerts may streamline some processes, they alone may not be sufficient to notably accelerate the comprehensive management of sepsis patients. Further strengthening connections between EMS and the ED is an ongoing effort within our group.

ADDITIONAL WORK: This AHRQ Patient Safety Learning Lab led to the creation of data infrastructure and resources (e.g., EHR data repository, ML models, platform for individualized audit and feedback) that have facilitated many projects not described here. These include EHR data-driven studies of infectious disease diagnostics performance,[9,10] in-depth study of acute kidney injury in the ED environment,[11–13] and development of a method to assess for bias introduced by missingness of EHR data – a common limitation to EHR-driven research in all of acute care medicine.[14] These data resources are propelling numerous other data science projects in various stages of development, including projects in pediatric infectious disease diagnosis and management, patient-reported outcomes for ED diagnostic performance, and implicit bias in EM.

Limitations: Though our multidisciplinary approach to improving ED care through data science has shown promising results, several limitations must be acknowledged. First, our findings and interventions were developed and tested within a specific healthcare system and may not be directly applicable to other settings without adaptation. The uniqueness of our data repository, driven by the specific demographics and operational practices of the Johns Hopkins School of Medicine, may limit the immediate transferability of our conclusions to institutions with different patient populations or resource availabilities. Second, the five-phase innovation cycle provided a structured framework for our projects but was time and resource intensive. Replication of our work under this framework by a less-resourced group may be challenging. Finally, our project suffers from limitations germane to all EHR-based projects. Although our granular EHR-derived data repository facilitated in-depth analysis, it also meant that our insights and interventions were limited by the data available. Inaccuracies or gaps in EHR data could potentially bias our findings and the effectiveness of developed tools. Moreover, rapid changes in healthcare practices, especially evident during the COVID-19 pandemic, may outpace the update cycle of our repository and tools, leading to decreased relevance over time.

Conclusion: The Connected Emergency Care Patient Safety Learning Lab made considerable strides in harnessing the power of data science to enhance emergency care. We employed structured innovation cycles and created a granular, EHR-derived data repository that is allowing us to close critical gaps in care, particularly in the management of infectious diseases within the ED. Our development and implementation of various data-informed CDS tools, including the innovative LOOP platform for feedback on patient outcomes, an antibiotic prescribing audit and feedback system, and use of ML to drive real-time CDS during the unprecedented COVID-19 pandemic, represent tangible outcomes of our efforts to improve patient care and safety. Our interventions have not only enhanced decision making in infectious disease management but also paved the way for more informed, efficient, and equitable healthcare practices.

List of Publications and Products

Peer Reviewed Original Research Publications:

1 Hinson JS, Zhao X, Klein E, Badaki-Makun O, Rothman R, Copenhaver M, *et al.* Multisite development and validation of machine learning models to predict severe outcomes and guide decision-making for emergency department patients with influenza. *J Am Coll Emerg Physicians Open* 2024;5:e13117. https://doi.org/10.1002/emp2.13117.
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Selected Peer-Reviewed Research Abstracts:

1. Badaki-Makun O, Hinson J, Levin S, Zhao X, Smith A, Klein E, Lau B. COVID Complications in Pediatric Patients: Machine Learning Models Identify Early Predictors of Severe Outcomes. (2023), SAEM23 Abstracts. Acad Emerg Med, 30: 8-423.

2. Hinson JS, Zhao X, Fenstermacher KZJ, Rothman RE, Badaki-Makun O. Multisite Derivation and Validation of Machine Learning Models to Predict Severe Influenza Outcomes in Emergency Department Patients. *Open Forum Infectious Diseases*. 2023; Suppl 10: 940.

3. Ehmann M, Hinson J, Morgan C, Clark K, Levin S, Balhara K. A Longitudinal Performance Portfolio Combining Real-Time Clinical Outcomes Data with Narrative Self-Reflection for Emergency Medicine Residents. *Western Journal of Emergency Medicine.* 2022; 23: 4.1.

4. Teeple S, Smith A, Toerper M, Levin S, Halpern SD, Badaki- Makun O, Hinson JS. Racism and Electronic Health Record Data: Missingness, Inequity in Predictions of a Machine Learning Tool. 2022 Annual Meeting Supplement. *Acad Emerg Med.* 2022; Suppl 1:S92-S93.

Selected Oral Presentations and Expert Panel Participation:

05/2024	Artificial Intelligence-based models Applied at Emergency Department Triage Predict Need for Admission and Critical Care Interventions in Pediatric Patients with Influenza. Oral Presentation (Planned). Society for Academic Emergency Medicine National Meeting, Phoenix, Arizona. Presenter: Xihan Zhao, MS
05/2024	Artificial Intelligence-based models Applied at Emergency Department Triage Predict Need for Admission and Critical Care Interventions in Pediatric Patients with Influenza. Platform Presentation (Planned). Pediatric Academic Societies Meeting, Toronto, Canada. Presenter: O. Badaki-Makun, MD, PhD.
11/2023	Proactive Engineering. Johns Hopkins University School of Medicine. Johns Hopkins Hospital, Baltimore, MD. Malone Center for Engineering in Healthcare Annual Symposium. Panelist: Jeremiah Hinson, MD, PhD.
11/2023	Artificial Intelligence: Is AI for the ED A-OK? Emergencies in Medicine. Grand Summit Hotel, Park City, Utah. Presenter: Jeremiah Hinson, MD, PhD.
10/2023	The Super Learner Ensemble: a Powerful Artificial Intelligence-Based Predictive Modeling Method for Identifying Patients at Risk of Poor Outcomes. Platform Presentation, American Academy of Pediatrics National Conference and Exhibition. Washington, DC. Presenter: O. Badaki-Makun, MD, PhD.
10/2023	Identifying Pediatric Patients at Risk of Developing Severe Complications from SARS- CoV-2 Infection – Harnessing the Power of Artificial Intelligence-Driven Predictive Models. Platform Presentation, American Academy of Pediatrics National Conference and Exhibition. Washington, DC. Presenter: O. Badaki-Makun, MD, PhD.
07/2023	Small Business and Innovation Research (SBIR) / Small Business Technology Transfer (STTR) Workshop Speaker Panel, National Science Foundation. Presenter: Scott Levin, PhD.
03/2023	Racism and EHR data: exploring missingness as a mechanism driving racial inequities in predictive performance of clinical decision-making tools. Society of Epidemiologic Research (SER) Mid-year meeting. Presented by Stephanie Teeple. Philadelphia, PA.
06/2022	Racism and Electronic Health Record Data: Missingness, Inequity in Predictions of a Machine Learning Tool. Society for Academic Emergency Medicine (SAEM) Annual Meeting. Presented by Stephanie Teeple. New Orleans, LA.

05/2022	Future of Precision Diagnostics in Emergency Medicine. Speaker and Panelist, Stanford Emergency Medicine Innovation Symposium (StEMIx). Virtual symposium hosted by Stanford Medicine (Stanford, CA) and delivered nation-wide via livestream. Panelist: Jeremiah Hinson, MD, PhD.
05/2022	Enhancing Emergency Care Through Artificial Intelligence: 6 Steps for Success. 2022 Society of Academic Emergency Medicine (SAEM) Annual Meeting. Half-Day Workshop. Presenter: Scott Levin, PhD.
04/2022	AI in Healthcare. American Health Information Management Association Webinar, Virtual. Presenter: Scott Levin, PhD.
03/2022	Development and Implementation of Artificial Intelligence in the Emergency Department, McGill University Emergency Medicine Health Informatics Grand Rounds, Virtual. Presenter: Scott Levin, PhD.
03/2022	Longitudinal Performance Portfolio Combining Real-Time Clinical Outcomes Data with Narrative Self-Reflection for Emergency Medicine Residents. Research poster presented by Kathryn Lorenz at the CORD Academic Assembly. 2022. San Diego, CA.
04/2021	Rapid Translation of Data Science to Clinical Practice, *Informatics Grand Rounds*, Johns Hopkins School of Medicine Division of Health Sciences Informatics, Virtual.
04/2021	COVID-19 Clinical Decision Support for Emergency Departments, Uniformed Services University, National Center for Disaster Medicine and Public Health, Critical Healthcare Infrastructure and Operational Modeling, Virtual. Presenter: Scott Levin, PhD.
02/2021	Data-Driven Decision Support for the Emergency Care Environment. Johns Hopkins University School of Medicine. Johns Hopkins Hospital, Baltimore, MD. Department of Medicine Grand Rounds. Presenter: Jeremiah Hinson, MD, PhD.
02/2020	Data-Driven Decision Making for Infectious Disease Management in the Emergency Department. Society for Academic Emergency Medicine (SAEM) Continuing Medical Education Diagnostic Symposium. Lecture hosted by SAEM (Des Plaines, IL) and delivered nation-wide via livestream. Presenter: Jeremiah Hinson, MD, PhD.
05/2019	The Secondary Use of Electronic Health Records for Research in Emergency Medicine. *Society of Academic Emergency Medicine (SAEM) Didactic*, Las Vegas, NV. Presenter: Scott Levin, PhD.
02/2019	Panel on Bringing AI to the Beside as a Commercial Venture: A New Paradigm, The Johns Hopkins Research Symposium on Engineering in Healthcare, Baltimore, MD. Presenter: Scott Levin, PhD.

Clinical Decision Support Tools and Resources Developed:

1. **Emergency Medicine Precision Medicine Analytics Platform:** A highly granular EHR-derived data resource that contains predictor and outcome data for every ED encounter within the Johns Hopkins Health System since 2017. Contained within a HIPAA-secure computing environment and overseen by the Johns Hopkins Institutional Review Board and Data Trust, this resource is used to facilitate clinical research by the Center for Data Science in Emergency Medicine at Johns Hopkins.

2. **Linking Outcomes Of Patients (LOOP) Outcomes Feedback Platform:** An EHR-derived web-based platform that facilitates personalized patient-level outcomes data to individual ED clinicians in a standard and automated manner.