IMPACT REPORT
ISSUE 22

Catalyzing Transformative Innovations in Health and Healthcare



Read the cover article on page 30

Duke Institute for Health Innovation



About DIHI

The Duke Institute for Health Innovation (DIHI) catalyzes transformative innovations in health and healthcare through implementation of high impact innovations, leadership development, and cultivation of a community of entrepreneurship.

We bring innovative solutions to the most pressing challenges in health and healthcare through multidisciplinary teamwork across Duke University and Duke Health and by fostering collaborations with national and international thought leaders.

DIHI IMPACT REPORT | Issue 22

Letter from the Directors
Page 3

Publications and Presentations
Page 54

DIHI Team
Page 56

2021 DIHI RFA Project Summaries

Transforming Epilepsy Surgery with Augmented Reality
Page 4

Development and Implementation of a Hospital at Home Program in Wake County
Page 6

A Unified Framework for Predicting Bacteremia and Interpreting Blood Culture Results
Page 12

Use of Convolutional Neural Networks in Skin Lesion Analysis for Dermatology Clinical Decision Support in Primary Care
Page 16

Machine Learning for Early Identification and Management of Pulmonary Embolism
Page 22

A Virtual Operating Room Hub to Facilitate Perioperative Communication
Page 24

Development of a Maternal Early Warning System Using Machine Learning
Page 26

Addressing Inequities in Organ Transplantation through Research and Innovation
Page 30

A Predictive Model for Assisted Triage of Traumatic Brain Injury
Page 34

A Population Health Strategy for NAFLD Using an E-Consult Platform and NLP
Page 38

Using Xealth to Manage Population Health and Engage Patients with Chronic Kidney Disease
Page 42

Using a Mortality Risk Predictor Model to Improve Advance Care Planning for Patients in the Hospital by Means of a Transitions of Care Toolkit
Page 46

DIHI PERSPECTIVES

10 The Science and Art of Machine Learning Model Deployment

14 Innovation Campfire

20 ALDIS: Timely Machine Learning Notifications

33 Monitoring Respiratory Syncytial Virus with Sanofi

45 Expanding DIHI's Impact through External Data Science Partnerships

48 Preventing Deterioration through Data Science

50 Walls Up before Hospital at Home

INNOVATION SCHOLAR PERSPECTIVES

5 Krunal Amin
9 Akash Patel
19 Samantha Wong
28 Namita Kansal
40 Leland Pung

DATA SCIENCE STUDENT EXPERIENCES

19 Connor Davis
21 Kai Deshpande
27 Megan Richards
41 Linda Tang

IMPLEMENTATION UPDATES

37 Sepsis Watch
41 SymMon
44 Chest Pain Assessment Tool
49 Pandemic Response Network



Thank You, Dr. Fulkerson!

We would like to thank Executive Vice President Bill Fulkerson, who, over the past nine years as Executive Director of DIHI, has helped to propel us to greater levels of excellence and impact. His clear vision for innovation, deep knowledge of the clinical enterprise, and unwavering focus on doing what is right for the patients and for our people have been inspirational. We are filled with gratitude for his outstanding leadership and support.

The DIHI Team

Letter from the Directors

Despite the obvious challenges of the past year, there were also many opportunities for us to advance and scale innovation in patient care - from enrollment of the first Duke patient to receive hospital-level care in the comfort of her own home, to using augmented reality in epileptic surgery to expanding the scope of two highly successful and responsive AI/ML models to predict adult sepsis and decompensation, to benefit our pediatric patients. None of these would have been possible without the remarkable talent and dedication of our frontline clinicians, staff, students and trainees. As we outline some of their achievements in this report, we would like to begin by expressing our gratitude for their service, resilience and commitment to excellence and impact.

Our innovation projects were focused on the following broad thematic areas:

- Novel strategies for care models to improve value of care delivery
- Enhancing provider and staff experience and wellbeing
- Enhancing patient engagement and experience
- Accelerating population health solution strategies

Of the 50 innovation proposals evaluated, ten were selected for implementation. Undergirding all DIHI projects that were funded and developed for implementation in our patient population was a strong focus on promoting health equity and eliminating disparities.

One of our principal areas of growth and success this past year has been in integrating AI and machine learning (ML) to inform patient care. Our faculty and staff are in the forefront of developing best practices for safe, effective and responsible use of AI in healthcare delivery settings. Models developed and implemented through DIHI have helped clinical decision-making for improved safety and quality while helping to alleviate clinician workload and understand underlying biases that may ultimately impact outcomes in diverse patient populations.

Looking ahead as we champion the vision articulated through Moments to Movement, we look forward to renewing our commitment to advancing health and racial equity and social justice. We seek to do this not only by developing, implementing, and scaling innovations for the greater good of all our patients and the communities we serve, but also by continuing to foster a diverse, inclusive, and compassionate environment where our extraordinary people are empowered to bring their passion, commitment, and authentic selves to work.

William Fulkerson, MD
Executive Director
Duke Institute for Health Innovation
Executive Vice President
Duke University Health System

Suresh Balu, MBA
Director
Duke Institute for Health Innovation
Associate Dean, Innovation and Partnership
Duke University School of Medicine



Transforming Epilepsy Surgery with Augmented Reality

Problem

According to the Centers for Disease Control and Prevention, 1.2% of the total U.S. population had active epilepsy in 2015.[1] One-third of these patients do not respond to pharmacological treatment and could benefit from epilepsy surgery.[2,3]

However, 40% of epilepsy surgery patients do not have long-term postoperative seizure freedom. Though there are a number of factors that affect surgical outcomes, one of the major problems is the difficulty in matching preoperative plans to the resection area in the operating room (OR).[4]

Before surgery, extensive preoperative noninvasive testing is done to determine the brain regions where the seizure originates. Though much work is done preoperatively, the neurosurgeon in the OR does not have any physical markers of the resection area. This problem is further complicated because all visualizations of the brain, including MRI, CT, or PET scans, and the electrophysiological data are on 2D computer screens. Though this data can be combined to create some 3D representations, for the most part neurosurgeons do not have easy access to these visualizations in the OR. They must create a mental 3D image to identify which seemingly normal-appearing brain tissue is causing seizures.

Solution

To bridge this gap of matching preoperative planning to resection area in the operating room, we used augmented reality to create a 3D hologram of the brain that can be used by the neurosurgeon.

TEAM
Muhammed Zafar, MD; Abhi Kapuria, MD; Matthew Vestal, MD, MBA; Will Ratliff, MBA

PROJECT IN BRIEF
In order to improve outcomes of patients receiving epilepsy surgery, the team developed an augmented reality application in order to create an interactive 3D hologram of the brain so that the neurosurgeon can better match their preoperative planning to the resection area once in the operating room. The app is now also being used for surgical planning, patient education, and teaching purposes, and it has the potential to be expanded to other use cases outside of neurosurgery.

Also, the neurosurgeon can interact with this hologram of the brain in order to orient themselves prior to surgery. Based on our market research and interviews with various neurosurgeons from Duke, there was a consensus that a device like this has the ability to help to define the seizure onset zone and potentially lead to an improvement in the resection area.

Ultimately, quick and easy access to all of this patient-specific data in a single application in the OR enhances surgical precision and accuracy. Furthermore, this platform has the potential to be expanded to other use cases; it can be implemented for many other types of surgeries or other OR settings and departments beyond neurosurgery.

Outcome

We were successfully able to create an interactive 3D hologram from MRI images as well as an application to render and interact with this hologram in real-time via our augmented reality devices (Microsoft HoloLens 2).[5]

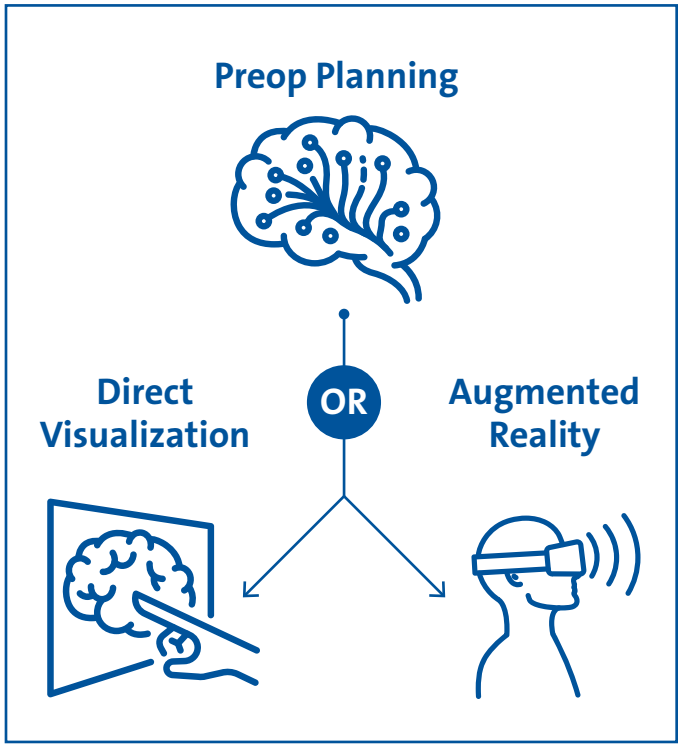
We are working to refine the user interface, followed by accurate registration of the 3D model with the patient's anatomical landmarks superimposed in the operating room to support the neurosurgeon during surgery. We also started using the Duke augmented reality app for surgical planning, patient education, and teaching purposes.

Next Steps

We filed an IND at the beginning of the project. Now, once the IP rights are secured and the patent is approved, we plan to apply for external grants through the American Epilepsy Society and the NIH. Ultimately, we plan to advance this project to the next step of fully incorporating live electrophysiological monitoring into the application.[6,7] We have begun testing in the pre-operative planning phase, and plan to test this A/R solution during surgery in 2022. Our goal is to create a startup company or outsource our application to another augmented reality company. We also plan to test the prototype in animals with the long-term goal of FDA clearance.

Academic Output

We will be submitting to the American Epilepsy Society after securing IP protection.



DIHI INNOVATION SCHOLAR PERSPECTIVE

Krunal Amin



I was initially drawn to the Duke Institute for Health Innovation (DIHI) because I wanted to spend my research year working on projects that had a direct translational impact on patient care. During my time with DIHI, I worked primarily on developing a natural language processing model for early identification and risk stratification of pulmonary embolism. As a scholar, I had the opportunity to lead multiple aspects of the project, including model development, stakeholder interviews, impact analysis, and implementation.

I had little coding and data analysis experience prior to becoming a DIHI scholar. Throughout the year, I was able to develop these skills with tremendous support from the DIHI team. The weekly journal club and fireside chats with physician-innovators enabled me to learn more about the health innovation landscape and think critically about the role I want to play in the future. DIHI has undoubtedly impacted my career trajectory. Moving forward, I feel confident in my ability to have a meaningful and productive career at the intersection of medicine, technology, and innovation.

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Development and Implementation of a Hospital at Home Program in Wake County

Problem

Duke Raleigh Hospital (DRaH) has many periods of high Emergency Department (ED) and inpatient demand. When the hospital is at maximum capacity, patients are boarded in the emergency room for a prolonged period of time until beds become available. Furthermore, patients who would normally be accepted as direct admissions may be diverted to other hospitals with available inpatient beds. Patients who spend days in beds for acute but non-intensive care accumulate similar fixed costs per day as intensive care patients. This is not optimal patient care. When the COVID-19 pandemic began in 2020, these problems worsened. Furthermore, we observed that patients were more hesitant to receive their care within the hospital, away from their families.

Solution

We proposed piloting an innovative care delivery model called Hospital at Home (HaH) as a potential solution to alleviate capacity and access problems, especially during public health emergencies. HaH allows patients to be treated for acute, hospital-level conditions in the comfort of their own home. Prior to 2020, a handful of health systems across the country developed and implemented this model; the most well-known of these systems are Mount Sinai, Brigham and Women's, Johns Hopkins, and the Veterans Affairs System. This innovative solution allows health systems to provide high-quality, low-cost care to patients in the comfort of their own homes and helps with multiple problems that plague health systems today, such as high inpatient and ED volume.

TEAM

Vidhya Aroumougame, MD, MBA; Michael Spiritos, MD; Will Knechtle, MBA, MPH; Akash Patel; Anisha Chandrimani, MD; Christopher Fiander; Stuart Smith; Fabian Stone; Gloria 'Pam' Porter, MSN, RN; Suresh Balu, MBA

PROJECT IN BRIEF

Acute Hospital Care at Home, or Hospital at Home, is an innovative care delivery model that aims to provide hospital-level care in the comfort of a patient's own home where they can be surrounded by a familiar environment and their family and friends. Our project developed an infrastructure for this model and tested it for one patient at Duke Raleigh Hospital.

More than a decade ago, the Veterans Affairs System found that this care model decreased hospitalization-related complications, improved patient satisfaction, and lowered overall healthcare costs.[1] Similarly, Mount Sinai published the results of a 3-year trial of their HaH program, in which they found that the patients enrolled in their program experienced shorter hospital length of stays, lower readmission rates, lower ED revisits, and decreased admissions to skilled nursing facilities. These patients also had higher patient satisfaction ratings.[2]

With Centers for Medicare and Medicaid Services (CMS) support in November 2020, HaH became rebranded as "Acute Hospital Care at Home" (AHCAH). This name specified that HaH was not outpatient, observation, ambulatory, or recovery care in the home, but inpatient care with inpatient reimbursement (42 CFR § 412.33). CMS approved DIHI's plan and infrastructure to support AHCAH in January 2021.

We planned to treat DRaH patients who lived within 10 miles of the hospital and whose primary admitting diagnoses were: Pneumonia (PNA), Chronic Obstructive Pulmonary Disease (COPD), Asthma, Urinary Tract Infection (UTI), Cellulitis, or Congestive Heart Failure (CHF). Wake County Basic Life Support vehicles would transport patients and DRaH Food Services would deliver food if ordered. The patients would be equipped with remote monitoring devices to keep track of their vital signs. Physicians would visit the patient once daily in person and nurses would visit two to three times a day to collect labs and administer medications. Data would be collected and presented within the hospital electronic health record (EHR). Our goal was to show that AHCAH is feasible and a safe way of delivering care to our patients. We also aimed for AHCAH to improve patient satisfaction, serve as a model to determine resource utilization and cost, and decrease the overall cost of care.

We enrolled, admitted, and discharged our first patient in April 2021. The patient was admitted with COPD and pneumonia. Her home hospitalization demonstrated that this model is feasible, and we can safely provide hospital level care in the home. We also witnessed how satisfied and happy the patient and her family were to receive care in this way.[4]

Output

There were several material outputs that came from this project. A dashboard was developed that incorporated existing DIHI risk stratification tools and machine learning models (Figure 1), the patient's admitting diagnosis, and payor and patient demographic information to facilitate identification of eligible patients.

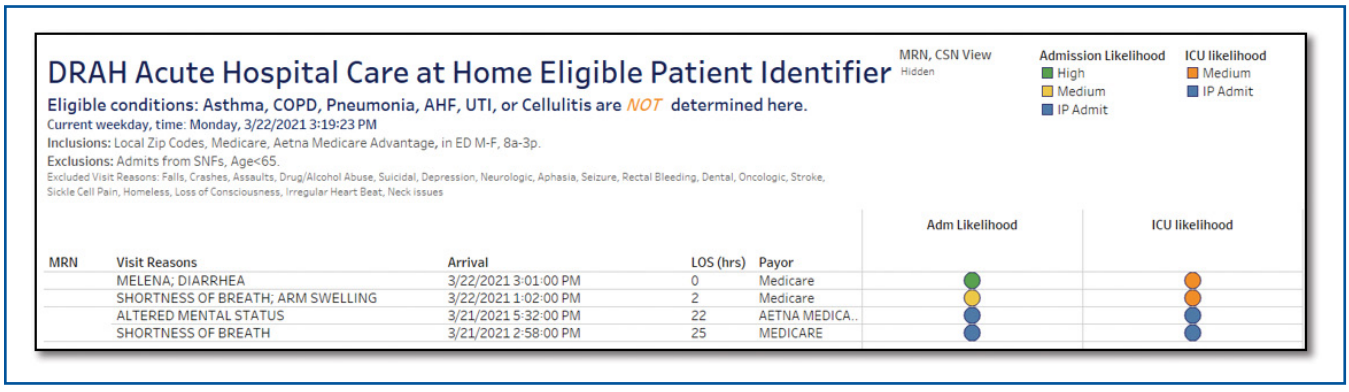
A 49-page playbook was developed detailing our workflows and processes that can be used by institutions within and outside of the Duke University Health System (DUHS) to implement their own AHCAH Program.

We established an Acute Hospital Care at Home department in Epic/Maestro Care that mimics the inpatient environment and allows those on the care team to place orders, document medication administration, and perform documentation. This allows for seamless continuity of care post discharge. We also filed a CMS emergency waiver, whose approval allowed us to treat our Medicare population. We developed brochures and patient education materials. We partnered with Duke HomeCare and Hospice, which provided our nursing staff. Finally, we began establishing vendor relationships to be able to have mobile imaging capabilities, which include X-rays and EKGs.

Continues on next page >

Standard of inpatient care:
- Two consecutive midnights of care
- Certified admission by licensed physician
- Care meets billable inpatient diagnosis code and DRG
- Patient has a complex history or comorbidities, severe signs or symptoms, current medical needs, or is at risk of an adverse event

Figure 1. Dashboard with an automated list of patients meeting primary Hospital at Home eligibility criteria. Uses DIHI machine learning models to sort whether the patient is likely to need inpatient admission or intensive care. Reflects current hospital status every 15 minutes.



Impact

The work accomplished by the entire project team laid the groundwork for similar programs to be implemented throughout the DUHS. A Hospital at Home "playbook" we created, combined with 87 hours of meetings we held with health system chiefs, revenue managers, and legal teams, equipped Duke Health clinicians and administrative leaders with positive information about peer programs, hospital at home jargon, and strategies (Table 1). In February 2021, this foundation gave a boost to the Enhanced Home Health for COVID-19 (EHHC) program, which quickly scaled up and provided care to COVID-19 patients during the pandemic, helping to relieve capacity constraints at Duke University Hospital. In the summer of 2021, Hospital at Home managers at Vanderbilt University Medical Center and Michigan Medicine reached out to our project team leaders for guidance. Furthermore, CaroNova and Ariadne Labs invited us to lead a Home Hospital Early Adopters Accelerator program across North Carolina.

Next Steps

We would like to continue this program for patients who would be best suited to receive their care in this way, with the goal of increasing our eligible patient volume. To do this, next steps include expanding our existing payor relationships, acquiring further imaging and technology capabilities, and extending staffing to more easily enroll patients Friday through Sunday. We plan to increase collaboration with other North Carolina early adopters of AHCAH programs.

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Academic Output

The project team has submitted a manuscript that analyzes the financial feasibility of the AHCAH model. Turn to page 50 for our perspective on challenges and lessons from developing and implementing this model.

Table 1: Conversations and real hours required to start conversations and sign-off on decisions.

Meeting Focus	Meeting Hours
Leadership	**40.00**
Core	28.00
Steering	10.00
CMS Application	2.00
Workflow	**26.00**
General Medicine / ED	18.00
Pharmacy	3.50
Nursing	2.00
Food	1.50
Case Management	0.50
Labs	0.50
Digital	**32.75**
General Strategy	13.50
EHR Partnership and Strategy	7.00
EHR Workflow	9.75
Remote Monitoring Devices	2.50
Scaling	**11.25**
Education	**10.00**
External Partnerships	**7.75**
Finance and Revenue Cycle	**6.00**
Risk, Compliance, and Legal	**4.75**
Supplies	**3.75**
Marketing	**3.27**
Grand Total of Meeting Hours	**145.52**

DIHI INNOVATION SCHOLAR PERSPECTIVE

Akash Patel



Working as a Duke Institute for Health Innovation (DIHI) scholar this past year has been a tremendously rewarding experience. Through my project with the Acute Hospital Care at Home (or Hospital at Home) program, I was exposed to entire areas within healthcare to which I had never been nor would likely ever have been exposed, such as finance, technology, compliance, and health system leadership. As part of the core project team, I had the immense pleasure of working with healthcare leaders throughout the Duke University Health System (DUHS). It was truly a remarkable (albeit sometimes challenging) experience seeing DUHS come together to help create a health delivery program that was not only imminently needed (i.e., to help with capacity constraints due to COVID-19), but was also one that could help address rising healthcare costs and improve patient outcomes in the long run. From my time on this project and at DIHI, I have fostered a newfound desire to be in healthcare innovation, particularly developing new healthcare delivery models.

Additionally, I believe that this year has diversified my skills beyond anything I could have hoped. As the co-lead of the logistics and operations team, I worked with over 100 individuals from various internal departments and external organizations such as nursing, hospital medicine, pharmacy, case management, home health, emergency medical services, and many more, developing higher-level leadership and management skills. Our collaborative work culminated in an extensive playbook that outlined the logistics needed to care for a patient in their home, from patient arrival to discharge. Furthermore, my work on the business model and financial analyses gave me a detailed view of hospital finances, resulting in a manuscript that is pending peer-review and publication. These financial analyses required deep dives into data science and Python coding, skills that have already been useful in other areas of my life and career. In hindsight, I cannot believe how much I have learned and been exposed to this past year. I am truly privileged and humbled to have been a part of the Acute Hospital at Home program. Thank you to everyone who has helped me on my journey this past year!

Team members prepare supply closet. Left to Right: Cynthia Macalino, RN; Pam Porter, MSN, RN; Justin Dixon, RN; Bonnie Bass, MPH





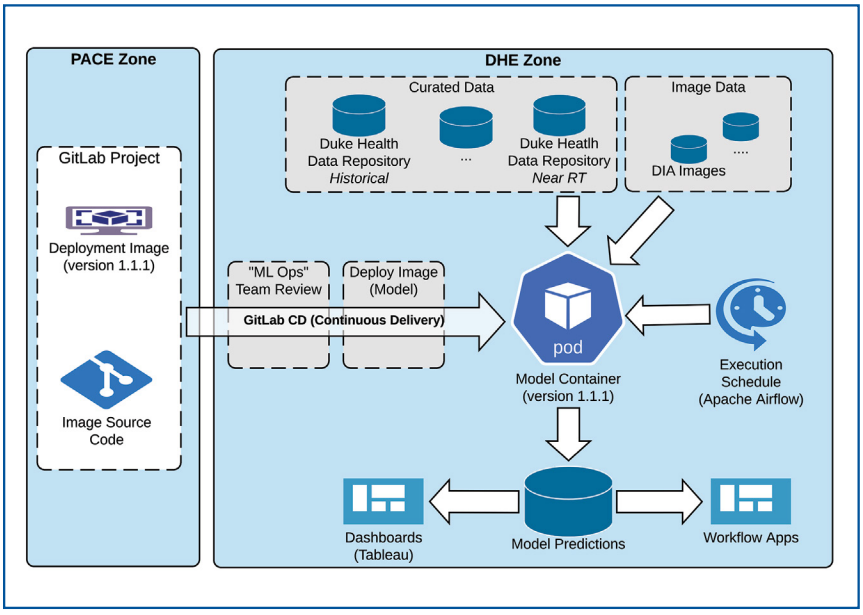
DIHI PERSPECTIVE

The Science and Art of Machine Learning Model Deployment

Marshall Nichols, MS

Machine Learning (ML) models create value only when they are deployed into production to enhance a workflow and they are actively consumed to solve a problem. The art of safe, effective, and efficient deployment of ML models in fast-paced clinical care has been simplified through practical experience of deploying many models over the past three years. We share our current observations, intuitions, and learnings.

Machine Learning models are expensive and time consuming—from design to development to integration to monitoring. Models require large amounts of curated and labelled data for training, more data for validation, and even more data for prospective evaluation of performance in a real-world setting.



The production of an ML model requires a small army of experts from various domains (clinical experts, AI/ML experts, statistical experts, data experts, solution design experts, software engineers, database experts, and implementation and change management leaders) to ensure that the inference generated by the model truly addresses the problem and that it performs as designed. Typical model development requires the lead data scientist to assemble code written by one or more ML experts and data engineers to consume the data and produce an inference engine which will produce an output that fits the workflow.

The path of many ML models stops here, at the point where the model exists and can be shown to work on new or a retrospective (held out) validation dataset. Manuscripts describing the development and retrospective performance are written, posters are developed, careers are started, and creative new ways to build features are shared with the world. However, the tool itself is often a stepping stone to something else, but it never sees true implementation and use in a clinical setting.

This is, in large part, because implementation of a model is equally expensive and complex as the development. Deploying an ML model into production requires entirely different sets of tools and capabilities, designed not for training and validating models, but for deploying code, orchestrating the solutions at the planned times, connecting and consuming inputs (data) from correct sources, producing inference, monitoring performance, routing alerts, providing insights, and directing the model outputs to planned destinations.

Familiarity with these tools is typically found, not among ML or content experts, but in the software product development community. These are typically software engineers, data and solution architects, database administrators, web app programmers, data engineers, and network specialists.

The ML experts and software developers often speak the same language but use very different dialects and routines. During ML development, emphasis is placed on input data structure, feature sets, and alignment of target outcomes. In this phase the code is often written in a very scripted way, with interactive figures and constant feedback on how well a model in training is performing. Typical ML code reads in a very linear and logical fashion that is fantastic for iteration by a small number of familiar individuals, primarily to improve performance. But this code can be difficult to test or build upon. After all, testing and extending ML code to do other things is rarely a need or a priority.

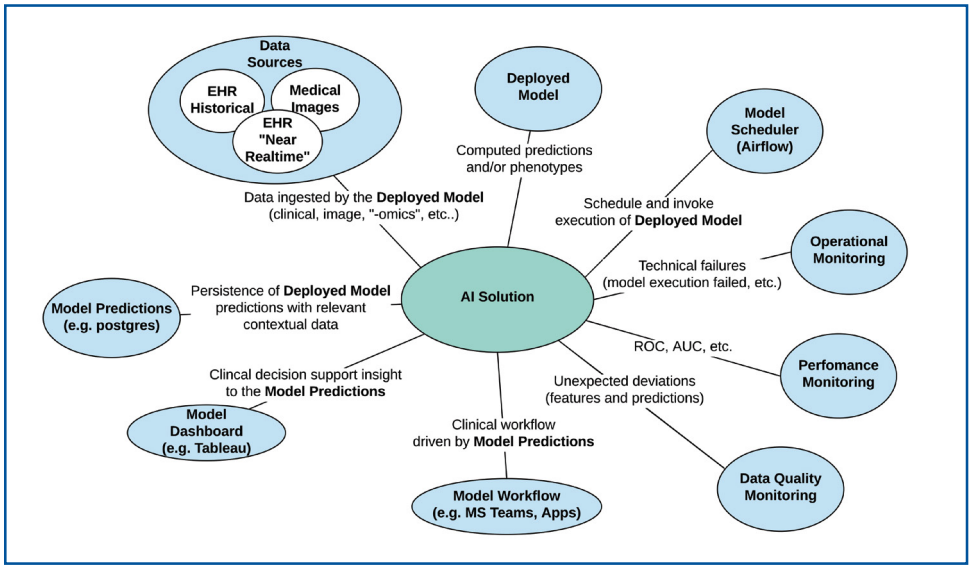
The requirements change for software developers and data engineers. Code is intended to be obvious in its intent at the function level, not at the script level. Codified tests get executed early and often in order to ensure quality and stability of the product being developed. Emphasis is placed as much on limiting the downtime of a tool (by maximizing the ease and speed with which updates can be made) as it is on monitoring the lifecycle of all parts of the implementation.

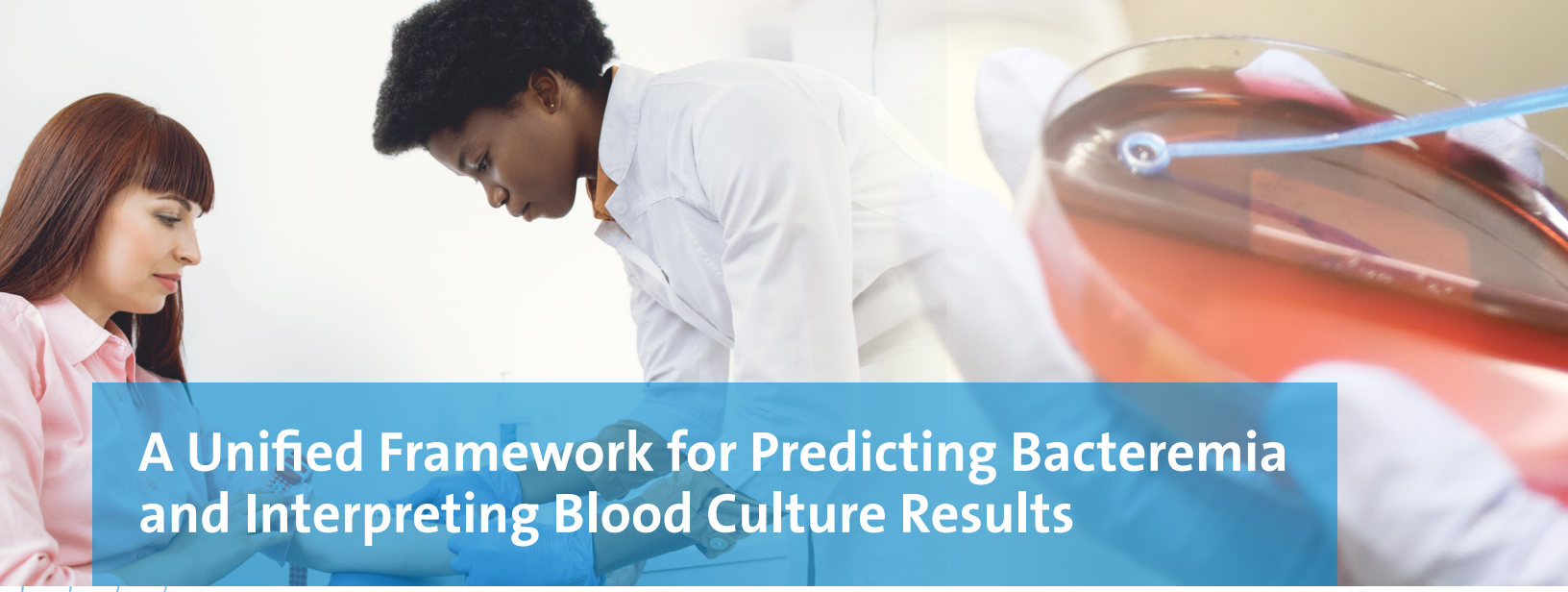
At the Duke Institute for Health Innovation (DIHI), we have deliberately focused our efforts to bridge these two worlds.

By bringing the software developers, data engineers, and database administrators into the ML process early, we have been able to lower the friction and cost to deployment, thereby increasing the translation of models from the concept/pre-clinical stage to 'ready-to-pilot' or clinical evaluation stage. Model code at DIHI is developed using many of the best practices in software product development, such as automated processes for checking tests, enhancing change visibility, and triggering automated deployment. Our data engineers have become intimately familiar with the ML model training and validation process and actions. This experiential knowledge has helped us to optimize source data delivery and the collection of meaningful output during both the training and pilot phases of model implementation.

This cross-pollination of experience has greatly condensed our development and deployment timelines while improving solution robustness. Keeping ML and content experts involved in the deployment and evaluation process enables us to receive rapid and critical feedback on model performance in the real-world setting. Adopting data engineering and software development best practices has set us up to iterate rapidly in order to address any concerns received throughout the lifecycle of the model. In 2017, DIHI invested the better part of the year just for a single (albeit complex) model implementation. Now, with our infrastructure and best practices in place, we push new model content into pilots weekly and can iterate on any previously deployed model with ease and speed.

We strongly believe that all models trained for integration into a clinical workflow should be approached as described above so that they can be deployed and maintained effectively and efficiently. They should be treated like first-class software products. That is, they should be implemented with automation and testing by data engineers and developed in concert with ML and content experts, all within the context of the workflow they're intended to improve. It is only in the context of the workflow that we can begin to meaningfully assess the quality, impact, and overall success of the model itself.





A Unified Framework for Predicting Bacteremia and Interpreting Blood Culture Results

Problem

Bacteremia is a common life-threatening condition with mortality rates as high as 37%.[1] Blood cultures are the gold standard diagnostic test but suffer from false negative and false positive results. Improving the status quo requires new tools to help clinicians solve two related tasks: (1) accurately quantifying a patient's risk for bacteremia, and (2) inferring whether blood culture results represent a true/false positive/negative.

Solution

We designed a statistical framework for quantifying an individual patient's pre-test probability of bacteremia as well as the probability of bacteremia given the results of a blood culture. Our approach uses two distinct but related models: (1) a pre-test probability model which quantifies a patient's risk of bacteremia in real time based on structured data available in the electronic health record (EHR), and (2) a likelihood model that quantifies the degree to which a patient's pre-test probability of bacteremia should be updated based on current and recent blood culture results. These two likelihood and pre-test models can be used in isolation to support clinician decision-making, or the outputs/predictions can be combined through Bayes theorem to calculate a patient's overall post-test probability of bacteremia.

Critically, applying these models at Duke requires first training the models on historical patient encounters where the true state of the patient (bacteremic or not bacteremic) is known. Yet, the true state of patients is not available in the EHR precisely due to the high false positive and high false negative rate of blood cultures.

TEAM
Christopher Polage, MD, MAS; Justin Silverman, MD, PhD; Michelle Nixon, PhD; John Bonnewell, MD, MSc; Will Ratliff, MBA; Mark Sendak, MD, MPP

PROJECT IN BRIEF
The gold standard test for bacteremia, blood cultures, has both a high false positive and high false negative rate. This feature of blood cultures leads to over- and under-treatment and unnecessary morbidity and mortality. This project develops statistical tools to aid clinicians in quantifying individual patient-level risk for bacteremia in the pre- and post-test setting.

To address this challenge, we implemented a sequential learning approach using ideas from the field of artificial intelligence. We assembled a multidisciplinary team of experts to select and estimate initial model parameters. The resultant models were used to predict the state of patients (bacteremic or not bacteremic) in past hospital encounters, with a subset of predictions that were validated through expert chart review; errors detected during this process were used to update model parameters. Through iterative application of this approach, we learned and validated the pre-test and likelihood models based on hundreds of thousands of historical patient encounters while requiring only a small number of expert chart reviews.

Impact

We have assembled a clinical training and validation dataset cohort of over 290,000 blood cultures performed in the Duke University Health System between January 2015 and December 2019.

Combined with a multidisciplinary team of experts in infectious disease, clinical microbiology, and statistics, we have developed a model to quantify a patient's post-test probability of bacteremia. This model considers a number of clinical factors (e.g., the use of IV antibiotics prior to blood draw) as well as test-specific factors (e.g., the organism(s) that were grown and the number of blood cultures collected and positive for growth). In addition to the current blood culture, the model also considers the results of prior blood cultures as well as initial gram stain results and other preliminary results to quantify the patient's current risk of bacteremia. This model is currently in its second round of iterative chart reviews and validation. Results from the first round found a sensitivity of 92.5% and a specificity of 100%.

Expert feedback has suggested other novel applications of this model beyond its intended use. Using a data mapping strategy, we can predict the final results of a blood culture given a preliminary Gram stain result. An example is provided in Figure 1, in which a clinician can visualize the probability that a Gram stain showing Gram-positive cocci in clusters will be Staphylococcus aureus or Coagulase Negative Staphylococcus and Methicillin susceptible S. aureus (MSSA) or Methicillin-resistant S. aureus (MRSA). In addition, by considering the individual probability of each of these organisms weighted by the probability that a blood culture resulting in that organism represents true bacteremia, we can calculate an overall probability of true bacteremia.

Beyond this current representation, we envision summarizing these results at a hospital-wide level as an antibiogram-like summary linking a microbiology result (Gram stain) to a clinical outcome of interest (final organism identification and likelihood of true bacteremia).

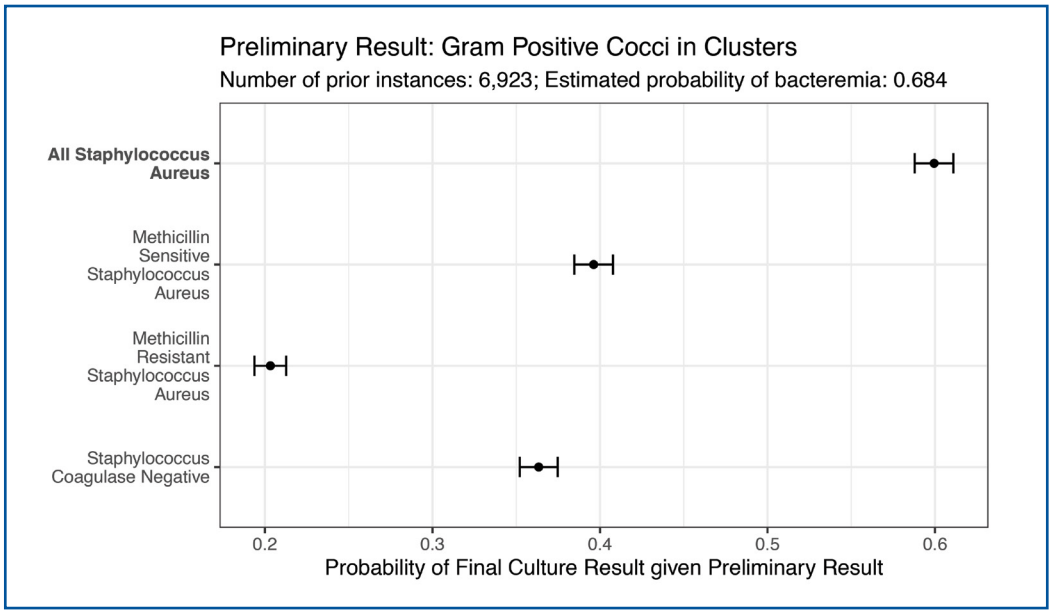
Next Steps

Our primary goal is to pilot and implement these models as clinician-facing decision support tools. With respect to the pre-test/post-test models, our next steps are to conduct two more rounds of chart reviews and then pilot an initial version of these models in selected hospital units (e.g., MICU, CTICU) so clinicians can use and explore the tool and provide feedback during prospective hospital encounters. After this additional prospective pilot evaluation and validation period, we plan to integrate the models and tools into the EHR. With respect to the Gram-stain interpretation and final blood culture prediction sub-model, our next step is to develop this as a quick-reference table for Duke clinicians. This quick-reference will make it easy for clinicians to predict the final result of blood cultures and likelihood of bacteremia given preliminary Gram stain results and initial organism identification(s).

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1. Coburn, B., et al., Does this adult patient with suspected bacteremia require blood cultures? JAMA, 2012. 308(5): p. 502-11

Figure 1: Example model output given a preliminary Gram stain showing Gram-positive cocci in clusters.







DIHI PERSPECTIVE

Innovation Campfire

Jamie Pollenz and Matt Wilson, RN

In keeping with its 25-year history of leading the way in clinical and translational research, the Duke Clinical Research Institute (DCRI) has implemented a new and innovative way for sourcing novel ideas in clinical research. In partnership with the Duke Institute for Health Innovation (DIHI), the DCRI launched Innovation Campfire, a program intended to leverage the incredible talent and creativity in the Duke Health community.

While 2020 brought many challenges, it also created opportunities for tackling issues in a new way. During this time, DCRI Executive Director Adrian Hernandez presented his senior leadership team with the idea of "Reimagining DCRI Research" by connecting DCRI's world-renowned clinical research to DIHI's innovation strategies. Hernandez, along with Suresh Balu, Associate Dean, Innovation and Partnership for the Duke School of Medicine and Program Director for DIHI, teamed up with operational partners and created Innovation Campfire. In the spirit of the television show *Shark Tank*, and modeled after DIHI's own Innovation Jam, the competition sought out cutting-edge ideas that would receive funding to launch groundbreaking clinical research projects.

In its inaugural year, Innovation Campfire received 18 submissions which focused on the following strategic priorities: (a) being leaders in real-world evidence/pragmatic trials, (b) leading the industry in hybrid/virtual trials, (c) building a novel real-world clinical research network, (d) shaping the future of delivery science, and (e) accelerating artificial intelligence/machine learning use in clinical research.

The field was narrowed down to eight teams who presented their ideas virtually to the DCRI community. Once the community vote was counted, six teams walked away with direct investments that totaled over $250,000. The teams have 12 months to create their solutions, meet project milestones, and implement their concepts.

One of the members of two winning teams, Neha Pagidipati, MD, MPH, assistant professor of medicine in cardiology, said, "The DCRI/DIHI collaboration is an excellent way to move forward ideas with a great degree of potential benefit which would not have gotten off the ground otherwise."

THE WINNING SIX TEAMS WERE:

1. Duke EMPOWER: A platform to Engage, inforM, Probe, prOmote Wellness, and fostEr community among patients with Rare diseases

Team: Aparna Swaminathan, Scott Palmer, Rosalia Blanco, Shelby Reed, Reed Johnson, and Mary Creed
Project Summary: Recruitment of patients with rare diseases (pulmonary fibrosis, or PF) in studies is challenging, and eligible patients are missed. Once the platform is developed, the team expects enhanced patient recruitment and increased research engagement as they increase awareness of ongoing studies, connect patients to study teams, build a Duke PF community, provide general disease education, provide monthly updates in research results, and increase virtual rehab opportunities.

2. REACH: Reimagining Engagement and Access to Clinical and Health Services Research

Team: Julius Wilder, Satasuk Joy Bhosai, Mary Creed, and Guru Kora (Pluto Health)
Project Summary: Finding out about clinical trials is hard; there is a heavy burden for people to know what is out there. Furthermore, onboarding is prolonged due to poor data sharing, and it is difficult reaching out to patients. REACH is being co-developed with Pluto Health to build features that promote virtual enrollment into trials and provide a real-world data pipeline. The team is first working to build a network in North Carolina and Tennessee.

3. DCRI Repository for Research: An Agile Structured Repository for Research Data

Team: Kevin Anstrom, Benjamin Goldstein, Jack Shostak, and Sybil Wilson
Project Summary: Inability to access huge volumes of data, specifically historical/research data, plagues Duke and the DCRI. A repository of organizational data is key to moving forward in a new digitized landscape. The creation of a repository (Data Lake) with scaffolding (format) that has the ability to access and store data will enhance and/or create solutions for researchers. The team plans to use a proof-of-concept study already in progress.

"DCRI ignited a competition to generate ideas for the future of clinical research. And, in the spirit of One Duke, by collaborating with our colleagues at the Duke Institute for Health Innovation we are encouraging the best of the best to participate."

Adrian Hernandez, MD, MHS
Executive Director,
Duke Clinical Research Institute
Vice Dean, Duke University
School of Medicine

4. A Direct-to-Patient Digital Health Platform: Capturing Longitudinal Outcomes in Children with Congenital Heart Disease

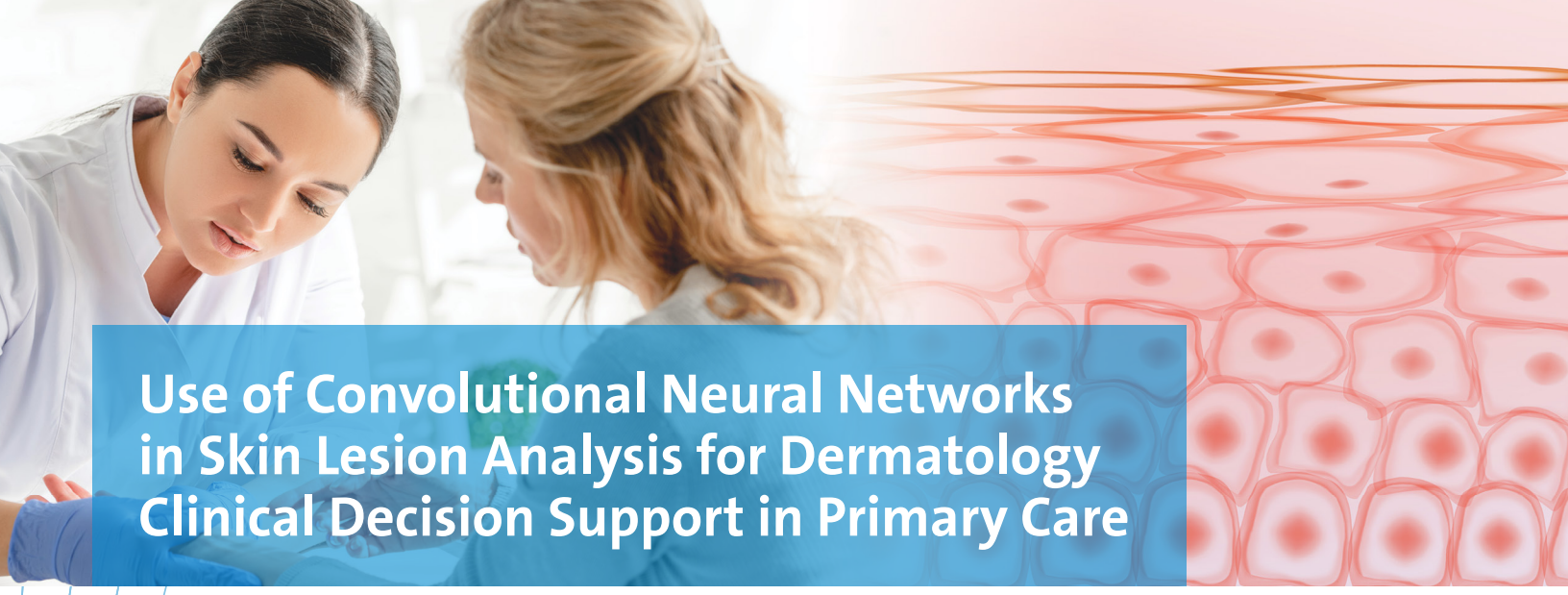
Team: Kevin Hill, Christoph Hornik, Anthony Cunningham, Jillian Hurst, and Mark Sendak
Project Summary: Congenital heart disease (CHD) has a lifelong impact and many potential therapeutic strategies but all are vastly understudied. This team's direct-to-patient digital health platform will capture longitudinal patient-reported outcomes and to link these outcomes back to existing CHD registries. This family-centered research platform comprised of multiple modalities includes a CHD app, electronic health record note templates, and email. These complimentary mechanisms will optimally engage families to capture the data that matters most to them.

5. Project Research Voice: Giving a Voice to Everyone Discovering Health | Putting the Boogie Back in Research

Team: Manesh Patel, Neha Pagidipati, Linda Lillis, Nishant Shah, and Sharon Califf
Project Summary: There is no easy platform for local clinicians and patients to generate media that captures their experience (their "voice"). In order to increase patient and research staff engagement, this team is creating a platform hosted by Duke/DCRI that allows patients, research staff, and clinicians to upload stories, testimonials, dances, and songs in TikTok-like videos to explain health science discoveries and innovations in a way that everyone can relate to and understand.

6. Accelerating the Delivery of Effective Treatments to Patients: Expanding Delivery Science at the DCRI

Team: Hayden Bosworth, Lesley Curtis, Neha Pagidipati, Megan Oakes, and Monica Reed
Project Summary: While many effective therapies exist, implementation is slow and ineffective. Despite the demand for implementation studies, the DCRI does not have a defined, cohesive implementation science offering. This innovative project will ensure that DCRI faculty and staff can respond consistently to implementation and delivery science opportunities at all stages of program development. The team is developing an implementation/delivery science offering that accelerates delivery of effective treatments.



Use of Convolutional Neural Networks in Skin Lesion Analysis for Dermatology Clinical Decision Support in Primary Care

Problem

Access to dermatology care is limited, with an increasing gap between supply and demand.[1] According to a survey study of dermatologists, the mean +/- standard deviation waiting time for an appointment was 33+/-32 days, with 64% of the appointments exceeding the criterion cutoff of three weeks for new patients and 63% of the appointments exceeding the criterion cutoff of two weeks for established patients. At Duke Health, the lead time is 34.3 days, and the most recently calculated wait time was close to 70 days. The concern is more significant post-pandemic and with a growing Medicare population, which is expected to account for 1 in 5 patients by 2030.[2] In our current dermatology practice at Duke Health, the Medicare population accounts for 50% of the charges.

Primary care providers (PCPs) can screen to risk stratify patients in real time. However, many PCPs have difficulty effectively evaluating dermatological concerns because of variable experience and training in dermatology.

Solution

A consistent decision support system can mitigate PCP screening variability and create a powerful risk stratification tool, leveraging our frontline network of providers to enhance access to quality and valuable care. Deep learning models, such as convolutional neural networks (CNNs), have been developed to classify various skin lesions with high sensitivity and specificity.

TEAM
Meenal K. Kheterpal, MD; Samantha C. Wong, BS; Christine Park, BA; Meng Xia, BS; Will Ratliff, MBA; Mark Sendak, MD, MPP; Suresh Balu, MS, MBA; Ricardo Henao, PhD

PROJECT IN BRIEF
Our team trained a convolutional neural network model to facilitate dermatologic clinical triage. This model used retrospective, biopsy-confirmed clinical and dermatoscopy smartphone images, with and without clinical data. The model is being tested in a primary care setting with prospective images with the goal to expand the field of tele-dermatology.

They demonstrate similar performance to dermatologists and superiorly to PCPs and nurse practitioners in classifying skin lesions.[3] In this study, we developed and compared CNN-based models trained on smartphone based clinical and dermoscopy images with histological ground truth, with and without structured electronic health record clinical data, tasked with classification of skin lesions.

Concurrently, we collaborated with DHTS and the Duke Digital Strategy Office to design and implement an e-consult workflow across four Duke primary care locations. The purpose of this step was two-fold. First, it enabled us to prospectively collect and evaluate our model on lesion images from Duke's primary care setting. The model's clinical validity was tested against board-certified dermatologists, and clinical utility was verified via ongoing prospective images collected in primary care settings.

Continues on next page >

Moreover, this step pioneered dermatology e-consultation workflows as a means to explore access improvements for Duke patients. Specifically, 11 malignant lesions were discovered and rapidly triaged in the first four months using this pilot workflow (see Figure 1).

Outcome

See Table 1 for results of the model testing. The two most important predictors for the clinical data-alone model were age at encounter and number of prior dermatology visits.

Three board-certified dermatologists classified a separate test set of skin lesion images as benign vs. malignant and classified the images into one of seven categories. The model correctly identified malignant lesions with an accuracy of 76.92% at a threshold of 0.5 against the three board-certified dermatologists, who correctly identified malignant lesions with an accuracy of 83.76%, 72.65%, and 74.36%, respectively. Additional clinical data did not significantly improve the CNN image model performance, which was comparable to the dermatologists' performance, validating utility of a real-time image-only clinical decision support tool.

Figure 1. Dermatology E-Consult pilot workflow.

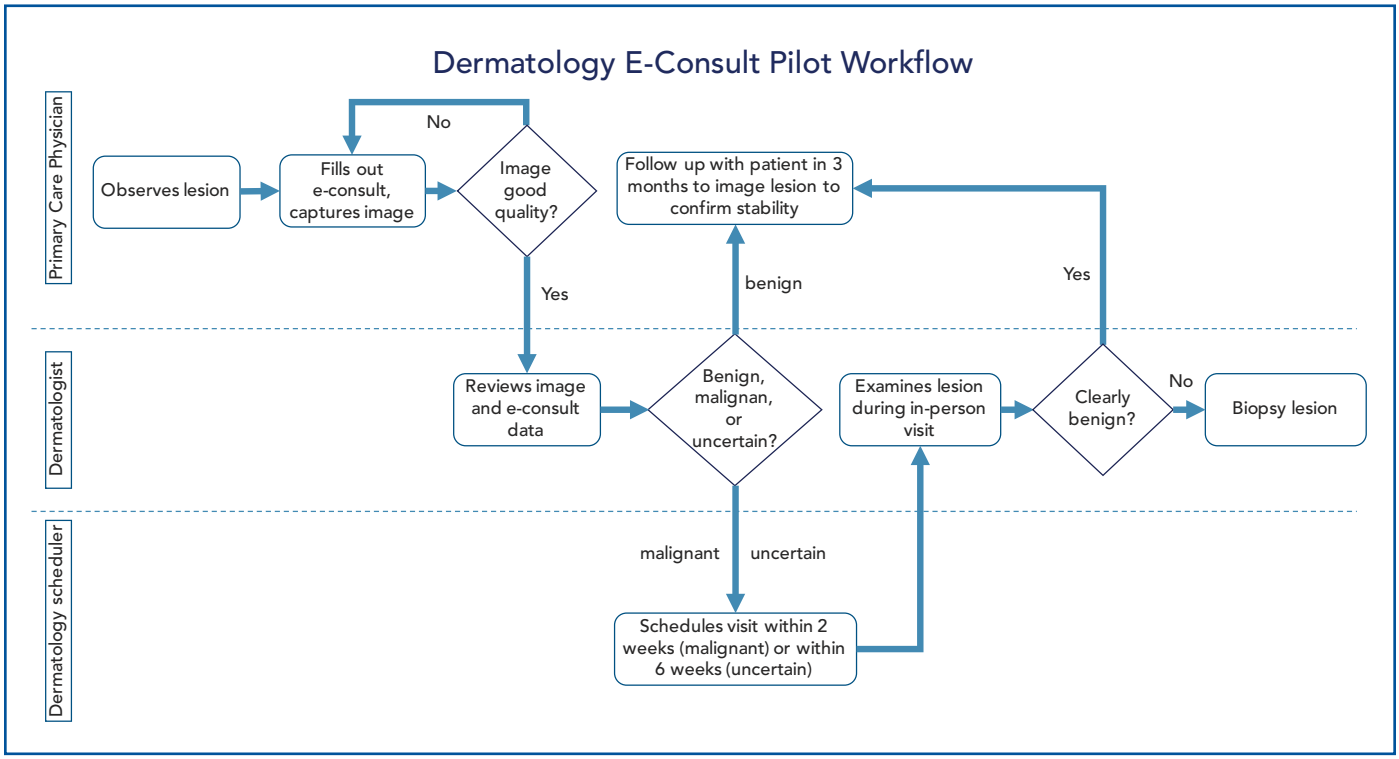
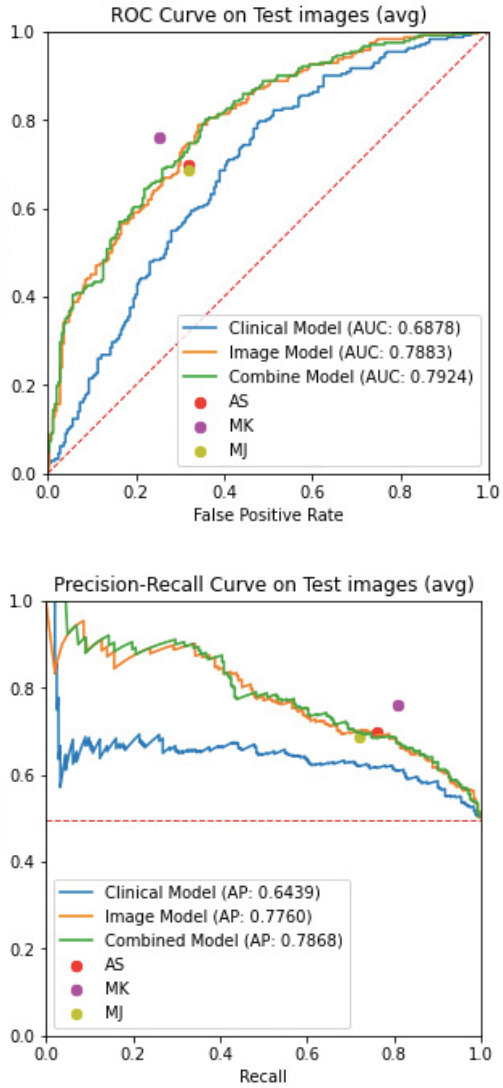


Table 1. Results of three CNN-based models used to classify skin lesions. Threshold was 0.5.

	Sensitivity	Specificity	Positive predictive value	Area under the curve	Average precision
Image-alone	82%	72%	73%	88%	91%
Image plus clinical data	82%	71%	72%	89%	91%
Clinical data-alone	80%	44%	57%	73%	71%

Figure 2 illustrates the three models' performance against that of the dermatologists. Once retrospective models were developed, we needed to test them prospectively. We prospectively collected clinical and dermoscopy images (n=182; 171 benign, 11 malignant) from primary care practices. Benign cases outweighed malignant cases so much that additional data and alternative threshold exploration is needed to fine-tune the predictive model.

Figure 2. Area under receiver operating curves (AUC) and precision-recall (AP) curves on test images; dermatologists' performance (AS; MK; MJ).



Next Steps

Upon prospective validation, our CNN-based models can be used to successfully aid tele-dermatology workflows to increase patient access to dermatology. Clinical and dermoscopy images (n=182; 171 benign, 11 malignant) collected prospectively from primary care practices were evaluated using the model, with sensitivity of 73% vs. 27% for model vs PCP, and specificity of 37% vs. 10% for model vs pcp respectively. The lower sensitivity for the model in the real-world data is explained by heavily skewed benign distribution, altered from the 50:50 benign to malignant ratio of the dermatology training set. Hence, additional data and alternative threshold exploration is needed to fine tune the predictive model. Future directions also include expanding paired clinical-dermoscopy image datasets and rashes for triage consideration, in order to expand the scope of our tele-dermatology workflow and our model outputs.

Academic Output

Wong S, Park C, Xia M, Ratliff W, Henao R, Kheterpal M. Use of Convolutional Neural Networks in Skin Lesion Analysis Using Real World Image and Non-Image Data. 2021 Machine Learning for Healthcare. 2021 Aug 6-7. Virtual.

Wong S, Park C, Xia M, Ratliff W, Henao R, Kheterpal M. Use of Convolutional Neural Networks in Skin Lesion Analysis Using Real World Image and Non-Image Data. 79th American Academy of Dermatology Association Annual Meeting. 2021 Mar 19-23. Virtual.

Xia M, Kheterpal MK, Wong SC, Park C, Ratliff W, Carin L, Henao R. Malignancy Prediction and Lesion Identification from Clinical Dermatological Images. Med Image Anal. Submitted.

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1. Suneja T, Smith ED, Chen GJ, Zipperstein KJ, Fleischer AB Jr, Feldman SR. Waiting times to see a dermatologist are perceived as too long by dermatologists: implications for the dermatology workforce. Arch Dermatol. 2001;137(10):1303-1307. doi:10.1001/archderm.137.10.1303.
2. THE NEXT FOUR DECADES:The Older Population in the United States: 2010 to 2050. May 2010; https://www.census.gov/prod/2010pubs/p25-1138.pdf.
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DIHI INNOVATION SCHOLAR PERSPECTIVE

Samantha Wong



In this past year as a Duke Institute for Health Innovation (DIHI) scholar, I worked on the Dermatology Clinical Decision Support in Primary Care project. In order to address the problem of limited patient access to dermatology providers, we developed a model to help classify skin lesions as benign or malignant. This model would help primary care providers, who oftentimes are the first to see such skin lesions, make decisions on whether or not to refer their patients to Dermatology. I was fortunate to have worked on the project prior to joining DIHI, so it was a rewarding experience to be able to carry it forward, from collecting images to train our model to seeing the model deployed in the primary care setting.

Prior to joining DIHI, I took several programming classes at the University of California, Berkeley, and taught students computer science as an undergraduate student instructor. I knew that I wanted to integrate computer and data science with medicine as a medical student at Duke, and DIHI provided me the perfect opportunity to do so. I was able to curate clinical data elements from the electronic health record in order to organize demographic and clinical features to help augment our dermatology image model. Serving as the liaison between DIHI and my clinical team, I helped my clinical team understand the various clinical features we were curating and relay their questions and ideas back to the DIHI team. We oversaw the development of a novel e-communication system that allowed primary care providers more rapid access to Dermatology, guiding their patient referrals. I also had the opportunity to help finalize a process to more efficiently organize medication data for future projects, and I worked on a COVID-19 tele-health utilization project. Fireside chats and journal club meetings also taught me concepts, such as change management and healthcare policy, which I would not have otherwise been exposed to in medical school.

As an aspiring primary care provider, I know how difficult it can be to manage a multitude of patients and their complex health conditions while providing compassionate care. I was inspired by seeing the preliminary results of the e-communication system guiding effective referral of patients to Dermatology, and I hope that our clinical decision support tool will one day be widely implemented throughout Duke primary care clinics. I believe that the continued development of similar clinical support tools will be able to ease the workload of primary care providers, freeing up their time to connect with patients and provide meaningful care.

DATA SCIENCE STUDENT EXPERIENCE

Connor Davis, MS



I am an AI Health Data Science Fellow working with DIHI on a number of projects related to transplant and the emergency department (ED). My work with DIHI began in 2019 with a project for generating a machine learning model to predict likelihood of admission for patients arriving to Duke emergency departments. Since then, my work on that project has expanded into developing models for predicting specific admitting service lines for patients, as well as validating ED triage models developed at other institutions on Duke's patient population.

My current work in transplant surgery involves generating a clinically interpretable DataMart for Duke's abdominal transplant patients; ideally, this data source can be used for developing future transplant related risk scores and models. As part of this, I am assisting with the DIHI RFA 2021 projects for generating lung transplant-related risk scores and analyzing equity among abdominal transplant patients.

In general, my interests lie in finding efficient and meaningful ways to marry clinical practice and data analysis for the improvement of patient care. Outside of my work, I enjoy cooking, working on home projects, and doing anything that gets me outside.



DIHI PERSPECTIVE

ALDIS: Timely Machine Learning Notifications

Matt Gardner, BS

The timely dissemination of machine learning (ML) model results, namely computed risk scores and/or phenotypes, are essential to improving care delivery and the health outcomes of patients in the Duke University Health System (DUHS). A standard component of a Duke Institute for Health Innovation (DIHI) model-driven solution is a Web-based dashboard. These dashboards are updated with model results and contextual data to inform care providers. Although invaluable, the downside is that Web dashboards need to be proactively checked by busy care providers. To supplement these dashboards, it is desirable to have model results that meet specified threshold criteria pushed to mobile devices in the form of email and/or pager alerts.

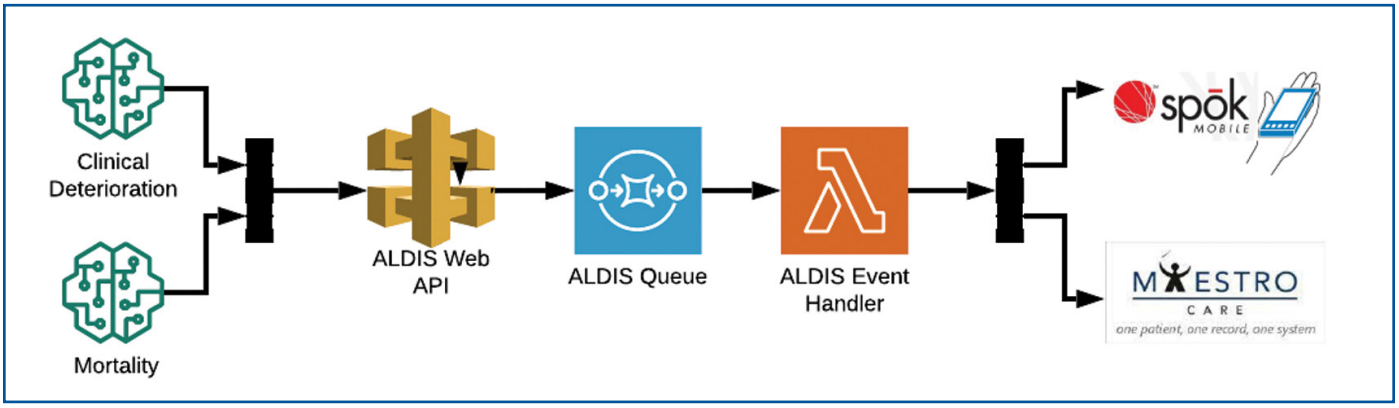
As a concrete example, for the DIHI HealthGuard model—which predicts the risk of mortality—when the model has identified a patient who may benefit from goals of advanced care planning, it sends an email notification to a centralized care team and pages the first call provider for the patient.

In this case, this notification functionality was built as an extension to the model code base. From a software engineering standpoint, it was clear that much of the functionality was generalizable, and a separate service would be optimal to provide this notification functionality across the portfolio of our model solutions.

Our DIHI engineering team embarked on building a generalized platform, referred to as an 'Analytic and Logic Driven Intimation System (ALDIS[1]),' that can be leveraged for handling notifications for data science, analytics, and ML projects. See Figure 1 for a high-level diagram.

A unified Web API captures computed risk scores and/or phenotypes reported by models; these are classified as notification eligible events by ALDIS. These events are enqueued for processing by event handlers. Event handlers process these messages and forward to the appropriate audience endpoint.

Figure 1. High-level diagram that depicts how model results flow into the platform, and, if they meet specific notification criterion, are delivered to one or more notification endpoints.



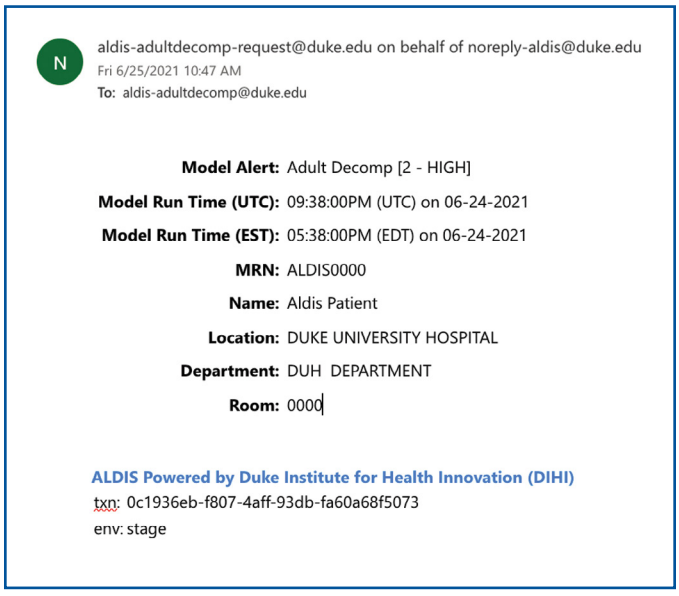
[1] *A hand-carried signal lamp used to flash messages, especially from ships and aircraft.*

Delivery can be in the form of a message sent to a mobile app, such as Spok Mobile, or structured data to be ingested by another institutional system, such as Maestro Care (Epic).

The ALDIS platform allows models to remain focused on their primary responsibility—computing risk scores and/or phenotypes—not determining when or how or to whom to send notifications. On the surface, sending notifications may seem simple, but there is considerable complexity that ALDIS encapsulates:

- Codified notification rules for each model (project) in one unified platform.
- Codified notification rules for each physical or virtual healthcare unit or service line.
- Standard templates for email and pager notifications.
- Utility functions for looking up care provider (e.g., First Call and Attending) contact details via Maestro Care APIs, such as pager numbers.
- Utility functions for delivering notifications, as well as structured data, to institutional endpoints, such as Duke eMail, Duke Spok Mobile, and GE CAREHub.
- Tracking of delivered notifications; this history is utilized to mitigate alert fatigue.
- Tracking model up-time, quality of data, or quality of service.

Figure 2. Example of a simple risk score notification message sent to the care team.



The DIHI Clinical Deterioration model provided a perfect pilot use case for leveraging ALDIS. The care team wanted to be notified when the model computed two consecutive "high" risk scores or a single "critical" risk score for a patient within a four-hour window. See Figure 2 for an example. Once notified about a patient, all notifications were to be silenced for the next four-hour window. These notification rules were codified into the ALDIS platform. The ALDIS platform proved to be effective in reliably sending and tracking prior notifications for patients. The prior notification history tracked by ALDIS was used to silence further notifications and mitigate alert fatigue.

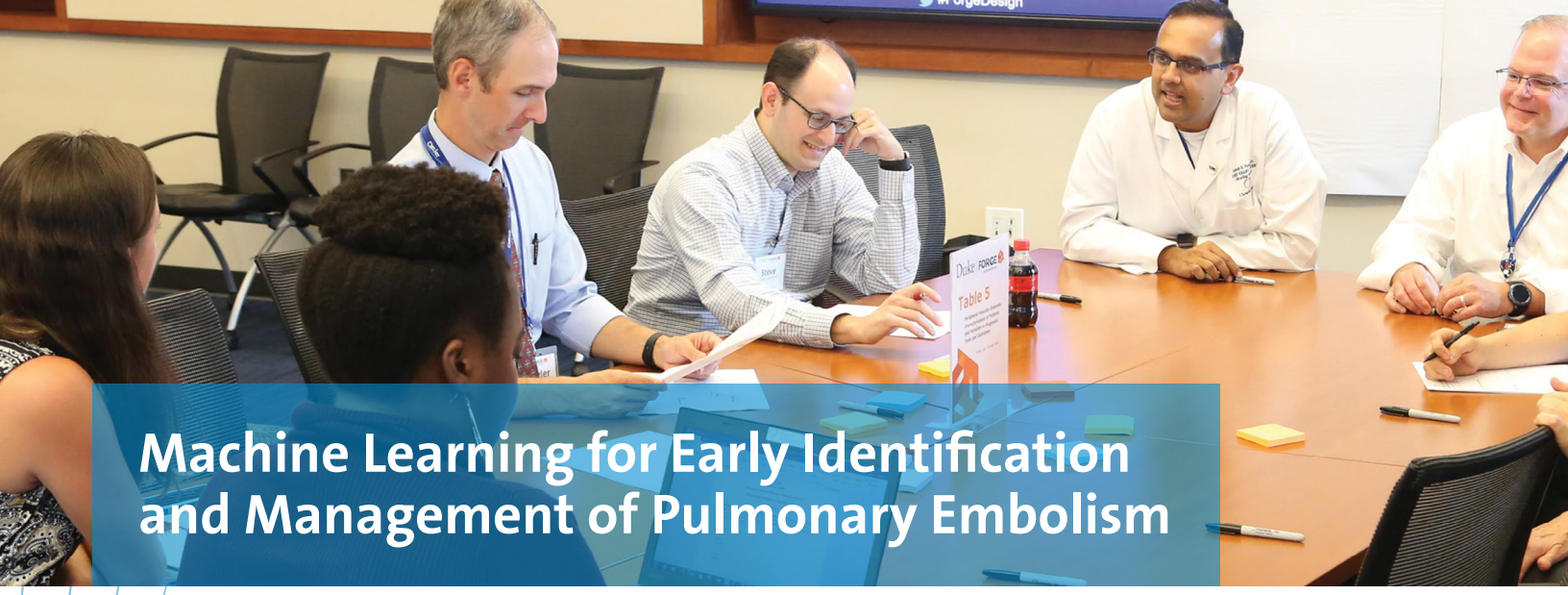
To supplement Web-based dashboards, it is desirable to have model results that meet specified threshold criteria pushed to mobile devices in the form of email and/or pager alerts.

DATA SCIENCE STUDENT EXPERIENCE

Kai Deshpande, MD



I am a Pulmonary and Critical Care fellow at Duke with a background in math. I'm doing an internship at DIHI as part of my research years to gain experience in big data, modeling, AI, and innovation. I am involved in multiple projects at DIHI. In my free time, I like to find new places to eat and new places to hike.



Machine Learning for Early Identification and Management of Pulmonary Embolism

Problem

Patients with acute pulmonary embolism (PE) may have a wide range of presentations, from asymptomatic to critically ill. Several risk stratification scores exist to identify patients more likely to decompensate and those who can safely be discharged home. We had previously found that more than half of acute PE patients admitted to Duke were low risk (and could have been safely discharged), and that less than half of patients with acute PE admitted to Duke had all of the labs and testing necessary for full risk stratification. The problem we are trying to solve, therefore, is to improve the safety and efficiency of acute PE care generally, including specifically safe discharge of patients with low-risk PE and adequate risk stratification of patients with non-low risk PE, to ensure that advanced therapies and monitoring are deployed as necessary to prevent deterioration.

Solution

For the pilot phase of this project, we have focused on safe and efficient discharge of patients with low-risk PE from the Emergency Department (ED), because achieving that aspect of PE care will improve identification of acute PE patients in need of better risk stratification while also reducing unnecessary costs and decreasing exposure to the risks associated with hospitalization. To achieve this, we developed a natural language processing (NLP) model to identify patients with PE in the ED as soon as the radiologist narrates their interpretation of the patient's chest CT scan. Once PE is identified, we calculate the patient's simplified pulmonary embolism severity index (sPESI), an existing standard of care at Duke for risk stratifying PE patients.

TEAM

W. Schuyler Jones, MD; E. Hope Weissler, MD; Krunal Amin; Will Ratliff, MBA; Anthony DiSpirito; Armando Bedoya, MD, MMCi; Alexander Sullivan, MD; Terry Fortin, MD, MS; Kishan Parikh, MD; Talal Dahhan, MD, MMEL; Sudarshan Rajagopal, MD, PhD; Samuel Francis, MD; Cathleen Bury, MD; Mitch Black, MD; Lacey Washington, MD; Jason Theiling, MD; Lauren Siewny, MD

PROJECT IN BRIEF

Our team is improving the care of patients diagnosed with acute pulmonary embolism (PE) in Duke's Emergency Department (ED), with a specific focus on preventing avoidable hospital admissions among patients with low-risk PE. We have formed a collaborative team of PE clinical experts, ED clinicians, radiologists, and DHTS colleagues to optimize care for these patients. Our project features three main components: a machine learning model to identify PE patients in real-time via CT scans and radiology narratives, an automated notification of front-line staff, and the creation of a rapid follow-up appointment workflow for low-risk PE patients to support their timely discharge from the ED.

We send this score and relevant patient information to the patient's attending ED physician via an automated notification. The ED physician then confirms the patient's risk and determines their ED disposition. To better support patients who are eligible for discharge, we have created a rapid follow-on clinic that the ED physician can refer a patient to for ensuring timely outpatient care. Figure 1 illustrates this pilot workflow for low-risk PE patients.

Figure 1. Pilot workflow for low-risk PE patients in the Emergency Department.

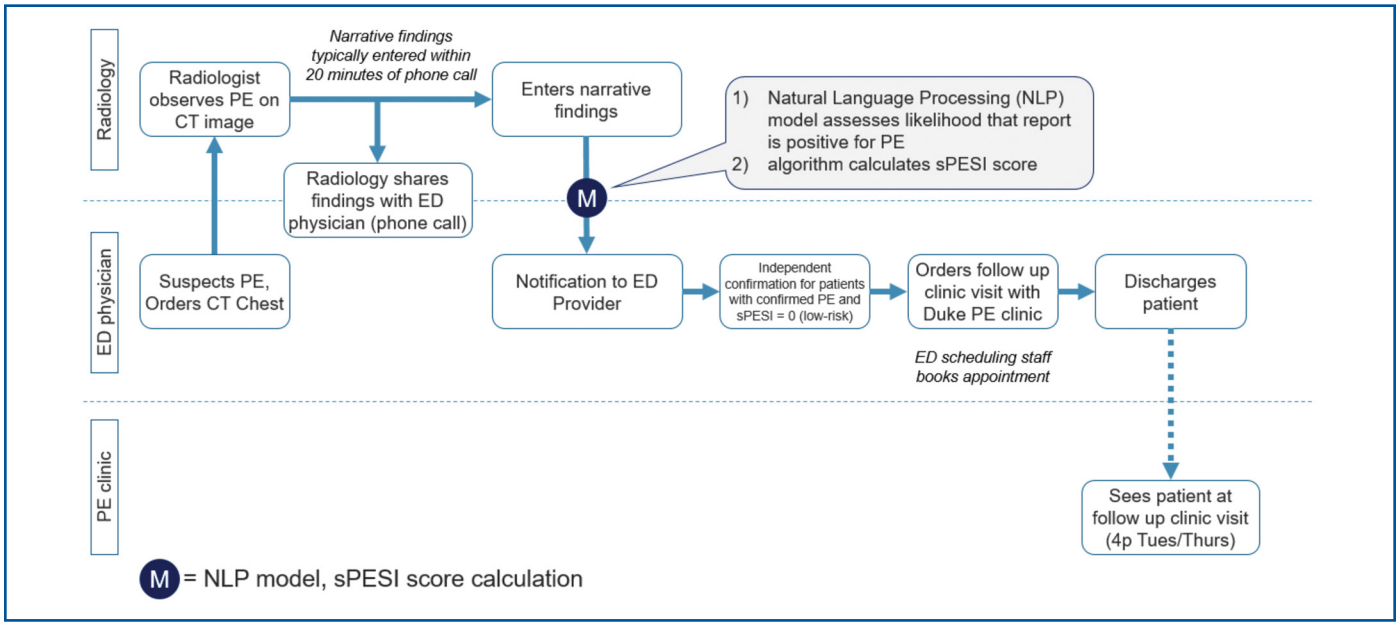


Table 1: NLP model performance for Internal Validation (Jun. 2018 - Aug. 2020; n=3,109 narratives) and Temporal Validation (Sep. 2020 - Dec. 2020; n=1,819 narratives).

Cohort	AUROC	AUPRC	Sensitivity	Specificity	PPV	NPV	F1
Internal Validation	0.99	0.98	0.87	0.99	0.96	0.98	0.92
Low-Risk PE (sPESI 0)	0.99	0.97	0.84	0.99	0.97	0.99	0.90
High-Risk PE (sPESI ≥1)	0.99	0.98	0.88	0.99	0.96	0.98	0.92
Temporal Validation	0.99	0.98	0.86	0.99	0.93	0.99	0.90
Low-Risk PE (sPESI 0)	0.99	0.97	0.76	0.99	0.96	0.99	0.85
High-Risk PE (sPESI ≥1)	0.99	0.98	0.89	0.99	0.92	0.99	0.91

Outcome

Our NLP model performs well at identifying PE from the radiologist's narrative, achieving an AUROC of 0.99 and an AUPRC of 0.97 in temporal validation [Table 1].

Utilizing the Duke Data Pipeline Platform, we are able to generate the model output and calculate the sPESI score calculation in real-time for driving automatic notifications. As of fall 2021, we are optimizing our notification mechanism for ED physician workflows and completing a silent launch evaluation of the model plus sPESI score, prior to pilot implementation.

Next Steps

We look to go live with our pilot solution in early 2022, and we will be measuring the number of patients for whom the model fires, adjudicating how often the model is correct in its PE identification and assignation of low-risk status, analyzing the numbers of patients with low-risk PE who are admitted to the hospital and who are discharged home with follow-up, and recording the proportion of scheduled follow-up appointments that are attended.

Next, we plan to expand the process to other hospitals in the Duke University Health System and to expand the model output to patients with intermediate-risk PE in order to ensure that tests and labs needed for appropriate risk stratification are completed.

Academic Output

Krunal Amin, E. Hope Weissler, William Ratliff, Alexander Sullivan, Michael Gao, Mark Sendak, Suresh Balu, Samuel Francis, Armando Bedoya, Lacey Washington, Mitch Black, Talal Dahhan, Schuyler Jones. Natural Language Processing for Early Identification of Pulmonary Embolism. Machine Learning for Healthcare 2021 – Clinical Abstract, Software, and Demo Track. August 6-7, 2021.



A Virtual Operating Room Hub to Facilitate Perioperative Communication

Problem

The operating room (OR) is a data-, cost-, and clinically-intensive environment in which patient safety is paramount. It is also a fixed, limited resource critical to delivering patient care. Optimizing patient safety while maintaining throughput to ensure timely delivery of care requires effective communication in the OR between key stakeholders.

Coordination between members of the clinical team and support staff in the OR is necessary to ensure delivery of safe and efficient peri/intraoperative care. Ideally, this communication would involve a semi-structured conference, or "huddle," at the start of each day in which all parties could be present to discuss case-specific needs, concerns, and current resource limitations.

However, given the diverse groups involved (including nursing, sterile processing, anesthesia, pharmacy, and surgeons), it is logistically challenging to hold this type of "huddle" consistently. In turn, information loss as a result of ineffective communication leads to potential delays in care, longer turnover times, and, worst of all, patient safety concerns—all while adding unneeded tension to an already stressful environment. Given the surgical volume at Duke University Health System, with over 70,000 operations completed last year, issues stemming from ineffective communication have the ability to compound rapidly.

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PROJECT IN BRIEF
Preoperative communication between all operating room (OR) staff occurs inconsistently and infrequently due to logistical constraints. The dissemination of case-critical information—including equipment needs, patient and staff concerns, and status updates—can be streamlined. Our team created a Virtual Operating Room Hub where all OR staff can communicate effectively. The result was improved patient safety, decreased OR waste, and enhanced provider and staff well-being.

Solution

In lieu of current inconsistently-implemented verbal "huddles," we envisioned that each OR have a corresponding virtual meeting place (the Virtual Operating Room Hub, or VORH) in which all staff and providers assigned to that room can communicate any special equipment needs, patient concerns, status updates, and critical information for elective cases beginning at the time of case-posting. In the future, support services would also have access to the VORH to share any concerns related to their specific domain (e.g., sterile processing communicating about equipment availability). Improving timely and accurate OR communication would allow all team members to be aware of patient-related concerns, reduce wasted supplies, increase OR turnover efficiency, and improve patient safety while simultaneously improving care-team morale.

Outcomes

The VORH concept was well-received by Urology and OR Nursing leadership. It entered production in February 2021 and went live on March 8, 2021. The team frequently presented beta versions to Urology leadership for feedback and to Urology faculty and nursing staff for iterative improvement. Super users were trained, and the VORH was piloted in Urology OR 32.

The VORH was integrated into existing Procedure Pass (Figure 1) and Status Board tools (Figure 2) currently in MaestroCare, and it is being integrated into the FlightBoard initiative as well. Procedure Pass includes case-specific task tracking with the additional opportunity to include free-text comments and clarifications.

Staff and provider focus groups were accustomed to recurring case-specific topics in which communication breakdowns or safety issues were frequent. These were then used to inform the design of the VORH section of Procedure Pass. Perioperative team members can chart the progress of case-specific tasks (e.g. “Started,” “Complete,” or “Not Needed”) as well as include free-text comments or clarifications.

Figure 1. Procedure Pass.

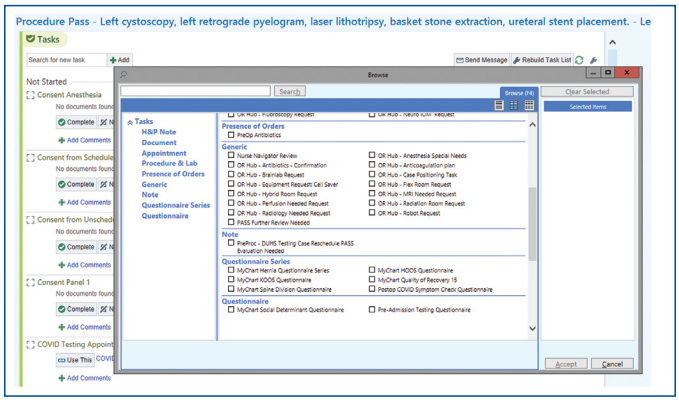
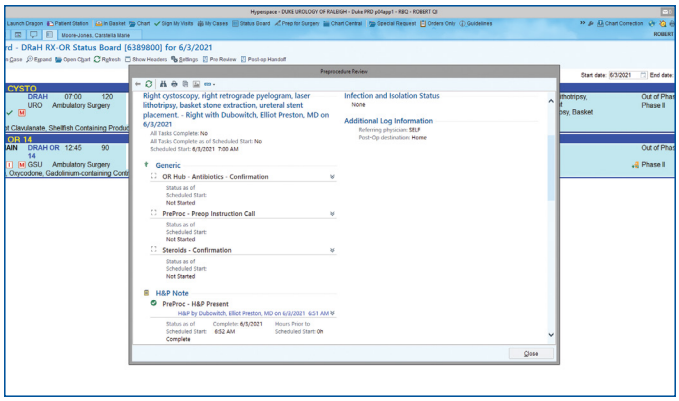


Figure 2. Status Board.

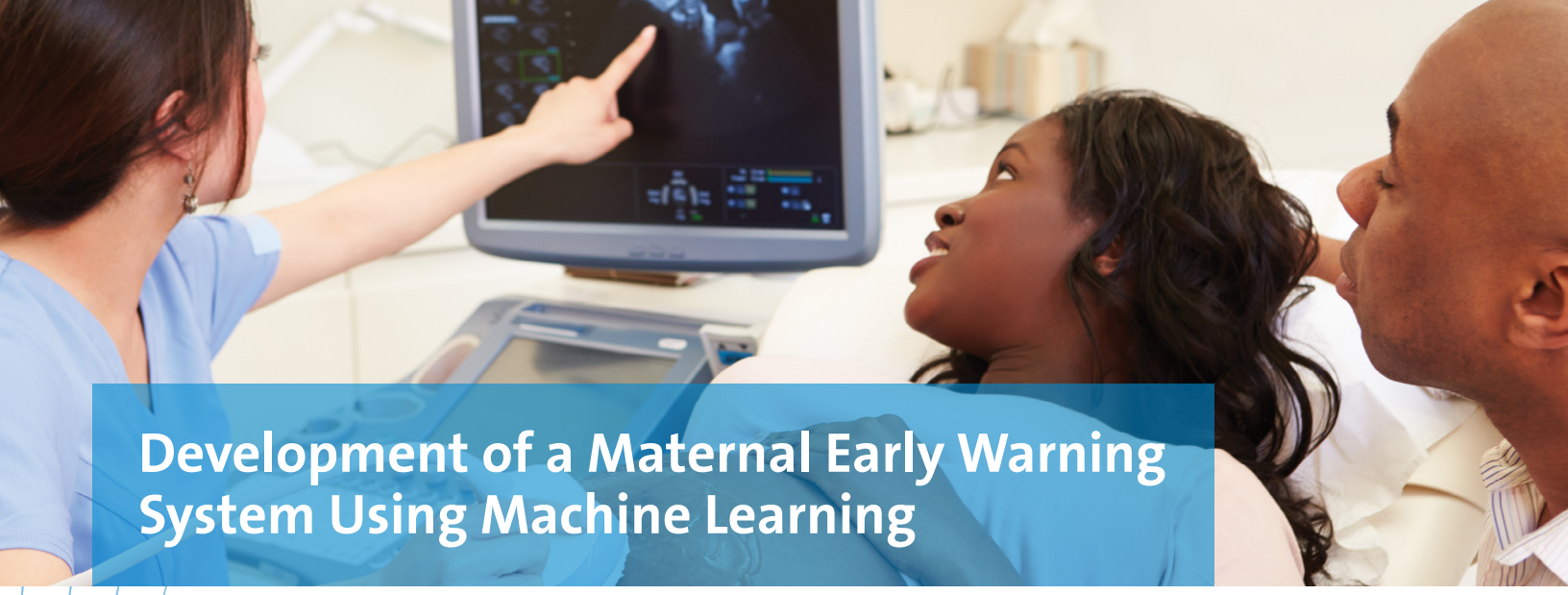


The VORH includes a status bar and printable pre-procedure reviews as helpful summaries. As Procedure Pass become integrated with FlightBoard, VORH information will also be available for intraoperative review. Urology OR 32 was selected as the pilot site for the VORH given the close working relationship between a consistent group of nurses and surgeons, a selective number of case types, and strong project champions. We anticipated these factors would facilitate more predictable adoption and rapid, open feedback to allow for iterative improvement and accelerated rollout to other ORs and working groups. However, surprisingly, VORH utilization was actually somewhat blunted by this choice.

The close staff/provider working relationships and easy access to supplies stored close to this particular OR disincentivized use of a new tool over ad-hoc verbal communication. However, utilization has risen with increased familiarity with the tool, better explanation of long-term benefits of streamlining OR communication, and continued encouragement and feedback. We anticipate that the addition of FlightBoard into OR 32 will highlight the benefits of the VORH by allowing better information preservation, anticipation of case needs, and increasing visibility. Overall, our project identified many common sources of frustration in communication among OR stakeholders. We demonstrated the feasibility of a technical solution to mitigate this, and we are continuing to find better ways to overcome the challenge of integrating this into current workflow routines.

Next Steps

We are continuing to refine the use of the VORH in OR 32 from both workflow and technical aspects. We anticipate integrating the VORH into FlightBoard, which will also be incorporated into both the OR 32 physical plant and workflow. Our next objective is to bring the VORH to the Pediatric General Surgery and other Urology ORs. This stems from the strong support expressed by faculty and staff, as well as the many specific needs and asks in the ORs that are not directly captured by current preference cards. Ultimately, we believe that the VORH would best benefit ORs and teams that have high case volumes, variable equipment use, and a moderate-to-high amount of staffing rotations. We aim to expand the VORH further once the technical and operational techniques are refined.



Development of a Maternal Early Warning System Using Machine Learning

Problem

The maternal mortality rate in the United States increased from 9.9 per 100,000 births in 1999 to 26.4 per 100,000 births in 2015,[1] making it one of the highest maternal mortality rates among industrialized nations. The leading causes of maternal mortality are hemorrhage, hypertensive disease, and thrombosis.[2] Severe maternal morbidity (SMM) is a significant indicator of maternal mortality risk and is defined by 18 indications of peripartum complications.[3] Blood transfusion is the most common indicator of SMM and likely related to postpartum hemorrhage.[4] SMM, like maternal mortality, also significantly increased over the last two decades, from 49.5 per 10,000 births in 1993 to 144.0 per 10,000 births in 2014.5 It is estimated that 40% of maternal deaths are preventable.[6]

Delay in diagnosis is a factor leading to SMM and maternal mortality,[7] prompting calls for the creation of early warning systems to quickly identify patients in need of care escalation.[8, 9] However, several systemic and technical challenges have inhibited the creation and adoption of such predictive systems in the United States. Commonly used clinical deterioration systems often excluded pregnant patients in the development process and perform poorly when adapted to the obstetric population.[10-15] Previous efforts to predict obstetric complications vary widely in the prediction task, complication definitions, and data used.[16] Significant progress has been made in using prenatal diagnoses to predict likelihood of adverse obstetric or fetal events at any point in the delivery hospitalization.[17-21] Current efforts at perinatal predictions (time-based predictions during the delivery encounter) are very limited but include prediction of postpartum hemorrhage and ICU admission for sepsis.[22, 23]

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PROJECT IN BRIEF
There are currently high rates of poor maternal perinatal outcomes at Duke University Health System (e.g., sepsis, hemorrhage, ICU transfer, and death). However, few risk models have been developed to predict these outcomes for the obstetric population. Our team aimed to use real-time data and machine learning models to predict deterioration in the inpatient obstetric setting. The project allowed physicians to respond earlier to high-risk patients and, in doing so, improved maternal mortality, ICU transfer, and readmissions.

Overall, we needed a Maternal Early Warning System (MEWS) to first identify obstetric patients at highest risk for SMM and mortality, and then to effectively integrate alerts into workflows to improve patient outcomes. Work needed to be done to improve upon previous prediction systems and adopt them.

Solution

Duke University Medical Center's Department of Obstetrics and Gynecology and the Duke Institute for Health Innovation formed a transdisciplinary team to develop a MEWS based on two solutions. The first was to use data updated to the latest 15-minutes to identify obstetric patients and present timestamps of the latest orders, procedures, lab results, vitals, or medications that warned of SMM.

The second was to develop and present outcomes from machine learning models for time-series prediction of eight SMM phenotypes: hemorrhage, sepsis, acute heart failure (AHF), acute renal failure (ARF), adult respiratory distress syndrome (ARDS), eclampsia, air and thrombotic embolism, and disseminated intravascular coagulation (DIC). Outcomes from both solutions were presented in a clinical dashboard, helping Rapid Response Teams (RRT) and designated staff within labor and delivery, OB triage, antepartum units, and postpartum units determine whether escalation of care was necessary.

Outcomes

Models were trained on data from a retrospective cohort of 19,419 perinatal obstetric encounters at the Duke University Hospital System, which are described in Table 1.1 and 1.2. The cohort contained 15,569 unique patients.

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DATA SCIENCE STUDENT EXPERIENCE

Megan Richards



I'm a senior at Duke studying Electrical and Computer Engineering with a concentration in machine learning and a Science and Society certificate in Digital Intelligence. My interests are mostly in machine learning and healthcare, as well as human-system compatibility and safety/bias/governance. This summer, I've been thrilled to work on DIHI's Maternal Early Warning System and Lung Transplant projects. I also sing in Duke's Chorale, am an RA, and help facilitate Duke's Effective Altruism ethics fellowship program.

Table 1.1: Cohort encounter summary statistics.

	Overall N= 15569	Hemorrhage N= 1380	Sepsis N=485	AHF N = 64	ARDS N=745	Embolism N=52	Eclampsia N=860	DIC N=46	ARF N=311
Median # Hours	58	21	21	30	15	28	6	15	27
1st Qrt / 3rd Qrt	39/75	8/41	12/36	16/67	7/30	5/54	16/32	7/33	8/45
% Positive	x	8.8	1.0	0.4	4.8	0.3	5.5	0.3	2.0

Table 1.2: Cohort patient demographics.

	Overall N= 15569	Hemorrhage N= 1332 (8.1%)	Sepsis N=478 (3.1%)	AHF N = 63 (0.4%)	ARDS N=708 (4.5%)	Embolism N=51 (0.3%)	Eclampsia N=832 (5.3%)	DIC N=46 (0.3%)	ARF N=294 (1.9%)
Mean Age (years)	29.8	30.13	27.93	30.2	29.81	28.07	30.56	30.891	29.95
White/Caucasian	6005	480	154	20	258	11	279	11	105
Black	4812	445	167	30	261	32	405	14	133
Asian	1128	90	40	4	52	2	23	11	13
Pacific Islander	0	0	0	0	0	0	0	0	0
American Indian or Alaskan Native	55	1	0	1	3	0	4	0	2
Other	1839	166	66	4	65	3	64	3	20
2 or More	1799	169	56	5	73	4	67	7	20

Table 2: Model performance across phenotypes.

	Hemorrhage	Sepsis	AHF	ARDS	Embolism	Eclampsia	DIC	ARF
AUROC	0.7657	0.91562	0.8367	0.8507	0.8109	0.8942	0.9228	0.8133
Baseline Average Precision	0.001000	0.000407	0.000075	0.000700	0.000058	0.000890	0.000040	0.000290
Model Average Precision	0.02768 (27X)	0.040280 (98X)	0.036410 (485X)	0.06043 (86X)	0.00212 (36X)	0.05437 (61X)	0.02031 (507X)	0.04385 (151X)

With machine learning approaches, we showed significant real-time predictive capability for all eight phenotypes, with AUROC scores ranging from 0.7657 to 0.9228, and average precision values between 36 and 507 times better than random guessing precision (Table 2). We evaluated several common sampling and weighting approaches to improve precision and found significant improvements, especially in extreme low-prevalence conditions.

We believe presentation of patients, warning signals, and risk predictions will enable more timely attention by medical staff, early evaluation and treatment of acute medical conditions, and quick and appropriate escalation of care. We believe that this will help decrease maternal morbidity and mortality among obstetric patients through prompt identification of patients at high risk of SMM.

Next Steps

Our next step is to view the MEWS outputs as a project team and verify that they meet prospective clinical practice and expectations. As a private group and without making clinical decisions, we will view the app in the context of our workflow both to review its accuracy and to refine how we have planned for the use of the dashboard to fit within the workflow. After this temporal validation, we will begin educating a larger team of prospective users about the MEWS and seek feedback. Finally, we will begin seeking approval for the MEWS as a clinical support tool and develop a longer-term plan to establish MEWS into routine practice.

DIHI INNOVATION SCHOLAR PERSPECTIVE

Namita Kansal



I had the unique opportunity to work as a third-year medical student research scholar with the Duke Institute for Health Innovation (DIHI) this past year. Through my project, I have collaborated with the DIHI team and the clinical team from Duke's Obstetrics and Gynecology Maternal and Fetal Medicine department to design and implement a machine learning model that will allow us to predict maternal deterioration on the Labor and Delivery floor.

Prior to this past year, I had little experience in Python and machine learning. I am very grateful to have been able to work with and learn from this incredibly talented team so early on in my medical career. DIHI has given me—unlike most of my peers—the chance to see firsthand how integral machine learning can and should be in the world of medicine. Although this past year in the pandemic prevented our DIHI team from working together in-person at the office, it was clear to see just how invested DIHI is in its trainees' growth and success throughout the year. I am continually amazed by the innovative and groundbreaking projects DIHI is eager to take on. This past year, I acquired not only technical skills but also life lessons in leadership, teamwork, and community engagement. I look forward to implementing these lessons in my own career and personal life!

Academic Output

On Sept 13, 2020, we submitted an abstract for the Machine Learning for Health conference, "Development of a Maternal Early Warning System with Machine Learning." This material was also presented during a semi-finalist grant review by the Gordon and Betty Moore Foundation.

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Addressing Inequities in Organ Transplantation through Research and Innovation

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Transplantation has been a durable treatment option for patients with end-stage organ disease for over 40 years. Organ transplant recipients benefit from prolonged survival, decreased comorbidities, and improved healthcare-related quality of life. Despite the well-established benefits of transplantation, the majority of patients with end-stage organ disease are never placed on the transplant waitlist. Disparate access to the transplant waitlist, combined with the scarcity of organs available for transplant, contributes to over 100,000 deaths from end-stage organ disease each year in the United States.

Inequities in access to organ transplant are longstanding.[1] Women, racial and ethnic minorities, and patients with public insurance, low educational level, and low income all have lower rates of listing for organ transplant.[2-13] Once on the waitlist, these marginalized populations also have higher rates of waitlist mortality and lower rates of transplant from living donors. Prior efforts to improve equity in access to transplant have focused on overcoming patient barriers with interventions such as web-based educational platforms, community engagement, culturally-tailored education, enhanced clinical teams (use of a social worker or health educator, etc.), and financial assistance. However, no patient-level intervention has led to a sustained, system-wide improvement in equity. This is likely because patient-level barriers fail to fully encompass the root causes of inequities in access to transplant.

Inequities in health care are influenced not only by patient characteristics but also by health system and clinical program characteristics. Institutional culture, location, resources, and complexity of processes have been shown to mediate inequities in several areas of healthcare.[14] To gain access to the waitlist for organ transplant, patients must navigate a multistep selection process that involves in-person assessments by several clinicians as well as diagnostic and immunologic testing. Ultimately, a multidisciplinary committee decides a patient's suitability for the transplant waitlist.

Disparate access to the transplant waitlist, combined with the scarcity of organs available for transplant, contributes to over 100,000 deaths from end-stage organ disease each year in the United States.

Few studies have elucidated how the complexity of the transplant selection process interacts with individual social conditions that burden patients as they navigate the process. These include accessing the initial medical care that generates the transplant referral, understanding the etiology of their disease, traveling to the center, and finding support for themselves and their families. The lack of advancement in this area is in part because there is no national data system or registry that reliably captures patients as they progress through the transplant selection process.[15] Equally likely is that the complexity and multitude of interactions and nuanced clinical judgements inherent in the transplant selection process cannot be fully captured with national data.

Health system-based innovation is foundational to improving equity in access to complex specialty care such as organ transplant.

It is unknown at this time which U.S. transplant centers achieve the most equitable access to the transplant waitlist for their patients. In fact, discerning which center-level disparities in access to transplant are true inequities is difficult due to differences in local population demographics, end-stage organ disease prevalence, and environmental factors.

As such, effective methods for ensuring equity in access to transplant while maintaining standards for post-transplant clinical outcomes remain largely unknown, and therefore impossible to disseminate as national best practices. These conditions together impel us to think and act locally. Health system-based innovation is foundational to improving equity in access to complex specialty care such as organ transplant. Our team is engaged in work built on a hypothesis that health systems and the processes by which they deliver care can be optimized for equity in order to mitigate the effects of structural, institutional, and interpersonal bias, similar to how they are standardized for safety in order to mitigate the effects of human error.

The transplant selection process varies widely in execution from center to center, rendering it vulnerable to multi-level drivers of inequities.

Clinician factors include variable medical decision-making, clinician-patient communication, and interpersonal bias. Transplant center factors include complexity and inflexibility of the donor and recipient evaluation processes, and disengagement with racial and ethnic minority and other historically marginalized communities.[16-19] Health system factors include staffing levels, payor contracts, and data infrastructure, including the electronic medical record.[20]

In the absence of a national data system, coalescing and mitigating the various drivers of inequities in access to transplant requires innovative solutions designed and executed from within health systems.

This is best achieved through:

- Multidisciplinary collaborations that capitalize on the expertise of clinicians, the power of health system data, and innovative design thinking that focuses on understanding the transplant selection process from multiple perspectives (organization, clinician, and patients);
- Challenging traditional assumptions inherent in candidacy determination; and
- Designing novel strategies for improving how the large amounts of data available within the health system data are assimilated and used for clinical decision making.

Ultimately, these solutions can be disseminated and adopted through cooperative efforts across major health systems that serve marginalized populations in a diverse range of conditions.

Health inequities are inextricably linked to structural racism, whereby historically marginalized groups are limited in their opportunities, resources, and wellbeing due to macro-level conditions.[21] In healthcare, these conditions are created at the intersection of clinician, center, and health system factors along with patient characteristics as patients navigate complex care pathways, such as the transplant selection process. Transplantation is a multidisciplinary specialty that delivers complex tertiary care in a system where demand overwhelms supply. Although all domains of healthcare are constrained by limited resources, the limited number of organ donors allows for a unique ability to quantify the limits of transplantation.

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As such, it uniquely suited to serve as a model system to study how complex healthcare processes and large multidisciplinary teams affect outcomes of high-cost, high-acuity patients amid the interactions between supply and demand, equity, and utility.

We may never eliminate patient-level barriers to complex care, like poverty, food insecurity, and cultural myths. We will also likely never eliminate subjectivity from its important role in complex decision-making related to high-cost tertiary treatments such as organ transplant. However, health system-based innovations are uniquely suited to achieve sustained improvements in health equity by redesigning systems and processes of care to focus on mitigating patient-level barriers while remaining resilient to institutional and interpersonal bias.

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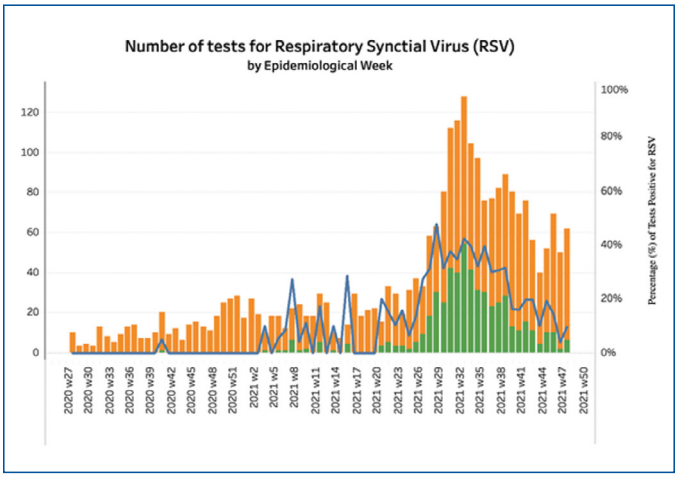
DIHI PERSPECTIVE

Monitoring Respiratory Syncytial Virus with Sanofi

Bradley J. Hintze, PhD

At Duke Health, we have a stated mission to "advance health together." The word "together" is crucial; it highlights the army of people required to fulfill the mission. There are doctors and nurses on the front lines and also staff and administrators ensuring that everything runs smoothly. In addition to providing healthcare today, researchers at Duke are actively advancing heath through translational research. This research, however, reaches much farther than North Carolina; Duke is fulfilling its vision to connect with the world to improve health globally.

At the Duke Institute for Health innovation (DIHI), we are crucial players in this work. Duke clinical researchers, in collaboration with industry partners, have enlisted our expertise in health data to move many projects forward. One of these exciting projects involves respiratory syncytial virus (RSV) in infants.



Green = Positive, Orange = Negative

RSV is a pervasive respiratory virus that, in most people, merely causes mild, cold-like symptoms. However, it can cause serious illness among older adults and especially infants. According to the Centers for Disease Control and Prevention, RSV is the most common cause of bronchiolitis and pneumonia in infants (less than 12 months).

Every year in the U.S., 58,000 children younger than 5 years old are hospitalized due to RSV. To combat this, Sanofi is pursuing a vaccine to protect against RSV. Sanofi has partnered with pediatricians at Duke to profile the health burden of RSV on infants throughout Duke Health. This collaborative project has a prospective and a retrospective component. DIHI provided the data required for these studies.

The prospective component sought to enroll patients in a clinical trial that would allow researchers to follow the patients in real-time. To do this, we set up an automated system that would identify patients younger than 12 months old who reported flu-like symptoms. Each morning, the system would automatically send an email to the researchers with detailed information on each patient who met the criteria for the previous day. The researchers would then use this information to identify and enroll eligible patients.

For the retrospective component, we set up a dashboard with patients under 5 years old who presented with a broad variety of acute respiratory symptoms. The dashboard presents data from 2015 onward and is updated daily. It displays longitudinal counts of both acute respiratory illness and lower respiratory tract infection encounters, as well as all RSV testing done at Duke Health. The dashboard has several filters, including age, gestational age, insurance, and care setting (inpatient, outpatient, telemedicine, urgent care, or emergency room). This dashboard has provided researchers valuable insights into historical trends of RSV in different populations.

This project with Sanofi is just one of many industry partnerships that DIHI maintains alongside Duke clinical researchers. The value of the data that we provide these projects cannot be understated. Health data is the currency that buys the empirical resources needed to advance research into clinical practice. DIHI is uniquely positioned to provide that currency to researchers.



A Predictive Model for Assisted Triage of Traumatic Brain Injury

Problem

Each year, an estimated five million Americans seek emergency medical care for traumatic brain injury (TBI),[1] a major cause of death and disability in the general population, and a leading cause in young adults.[2] TBI treatment is extremely time-sensitive, with better outcomes associated with expedited care, necessitating early diagnosis and categorization of injury;[3] if secondary injury (inflammation, bleeding, neuron death) is not arrested, patients can be left with profound mental and physical disability. While treatment guidelines are well-established for cases of severe trauma, they are less clear for mild to moderate TBI.[4] The latter are much more difficult to assess, as traditional CT evidence for TBI can take many hours to materialize[5,6,] if at all[7], with studies suggesting that for every positive mild TBI diagnosis, one goes undiagnosed (a "silent epidemic").[8] Thus a common strategy when diagnosing mild to moderate TBI is to admit borderline cases for further monitoring, but the sensitivity and specificity of this process is low.[9]

Solution

To reduce the impact of TBI misdiagnosis on patient outcomes and to reduce readmission rates within Duke University Health System (DUHS), our goal was to build a model that predicts with high accuracy, future patient disposition and integrate the model into the Emergency Department (ED) at regional DUHS hospitals, where the majority of ambiguous mild-to-moderate trauma cases are delivered, as a data-driven assistant to existing workflows for TBI triage.

TEAM

Timothy Dunn, PhD; Michael Haglund, MD; Anthony Fuller, MD; Brian Burrows, MD; Gavin Karr, MS; Christine Park, BS; Mark Sendak, MD, MPP; Will Ratliff, MBA; Matt Gardner, BS; Connor Davis, MS

PROJECT IN BRIEF

Diagnosing minor traumatic brain injury (TBI) is very difficult, and treatment guidelines for mild to moderate TBI are unclear. For this reason, many patients are admitted and held until more knowledge is available. We improved this knowledge by utilizing a neural network machine model on CT images and predicting likelihood of TBI complications. We now have more information to determine whether an intervention is required or the patient can be sent home. The model enables direct and well-informed care for acute TBI needs and should reduce rates of readmission.

Because traditional TBI decision making depends heavily on brain CT imaging data, our goal was also to establish a real-time CT image analysis pipeline that incorporated neural-network-derived image features to guide prediction.

To train our model, we pulled data for all DUHS TBI ED encounters between 2015 and 2019, forming a cohort of 102,239 encounters and 76,995 patients (Figure 1). We defined a TBI encounter as one with either a recorded ICD code for TBI diagnosis or a recorded chief complaint of head injury. Within the cohort, we found and pulled 50,074 brain CT images using a new framework we developed to improve archival data transfer speed and fidelity.

Figure 1. All DUHS TBI ED encounters between 2015 and 2019.

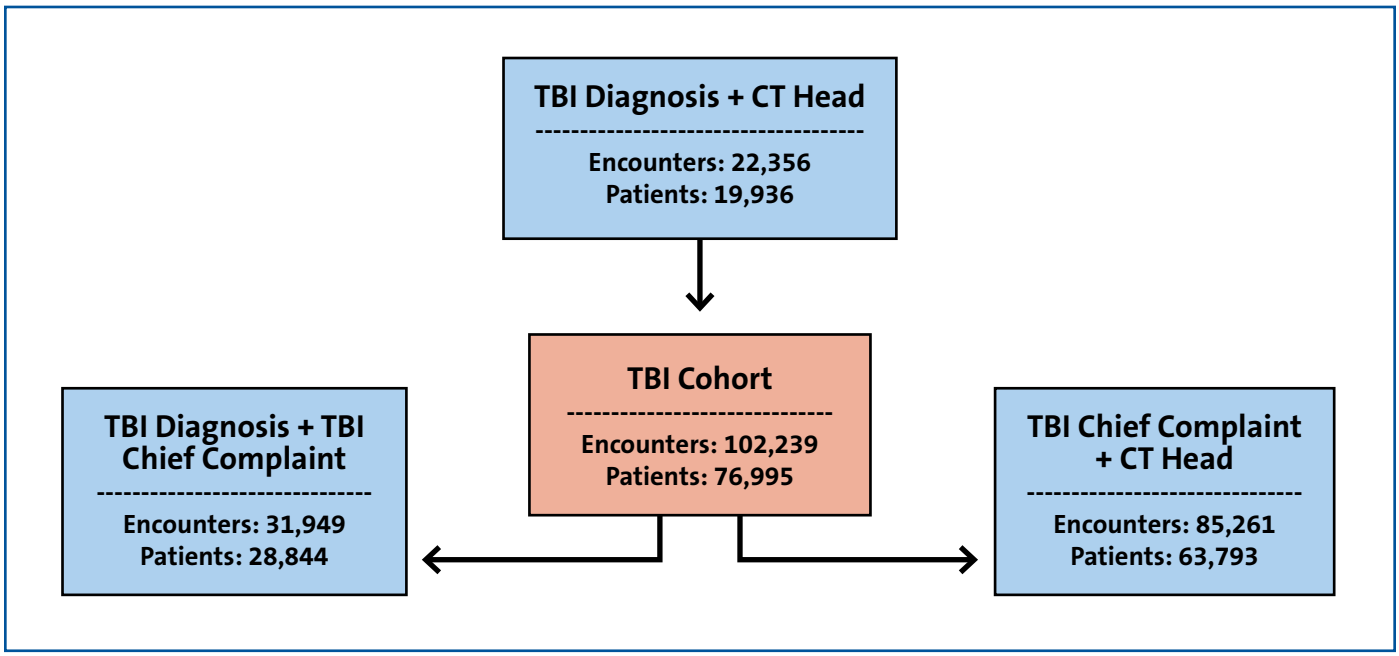
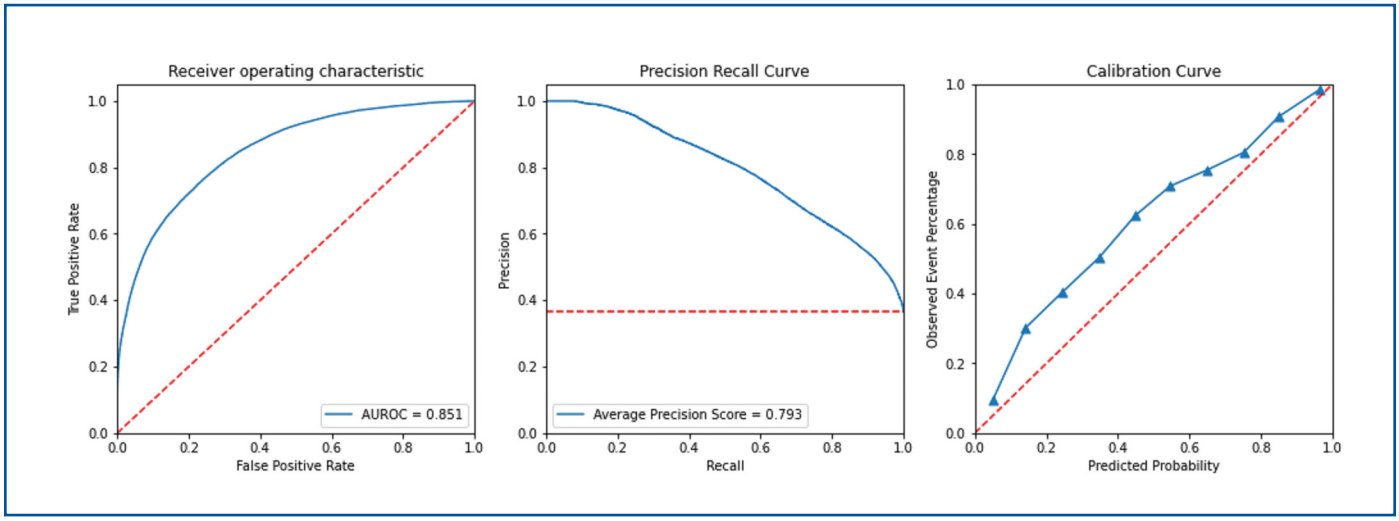


Figure 2. Inpatient admission prediction.



In conversation with clinical experts, we derived a set of outcome variables that would be most informative when making TBI triage decisions in the ED: ICU admission, inpatient admission, surgery, 30-day readmission, 30-day mortality, close follow-up, and GCS deterioration. We used these data to train a model (light gradient boosting machine) predicting ICU and inpatient admission probability only from ED data in TBI patients. We used brain CT imaging data to train an interpretable convolutional network (ProtoPNet, developed at Duke by Cynthia Rudin) that diagnoses intracranial hematomas while also indicating which regions in the image were instrumental for the network's prediction.

Outcomes

The team successfully developed a model predicting future ICU and inpatient admission from ED variables in TBI patients. For inpatient admissions, the model exhibited an AUROC of 0.851 and an average precision of 0.793 (Figure 2), and for ICU admissions it exhibited an AUROC of 0.765 and an average precision of 0.266.

Continues on next page >

Our Convoluted Neural Network (CNN) showed 0.94 AUROC (Figure 3) for automatically diagnosing hematomas from CT brain images. At a threshold of 0.85, the model achieved a sensitivity of 0.843 and a specificity of 0.815. It was able to indicate, via its interpretable output, the location of pertinent structural brain elements (Figure 4).

Figure 3. ROC for slice-by-slice classification of large hematoma in ED patients suspected of suffering TBI.

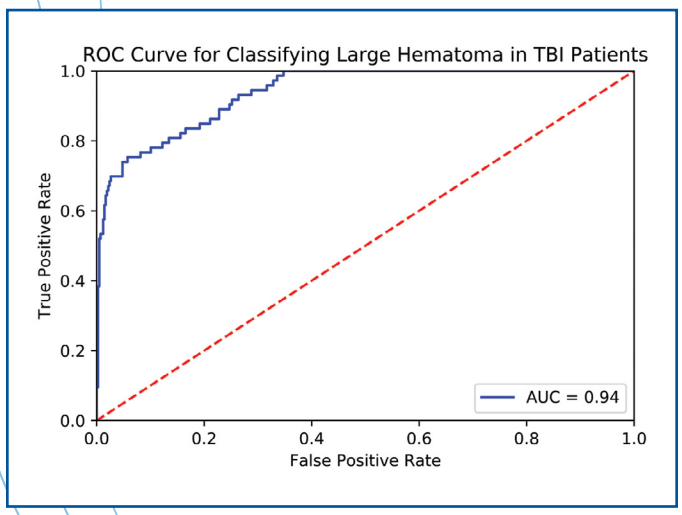
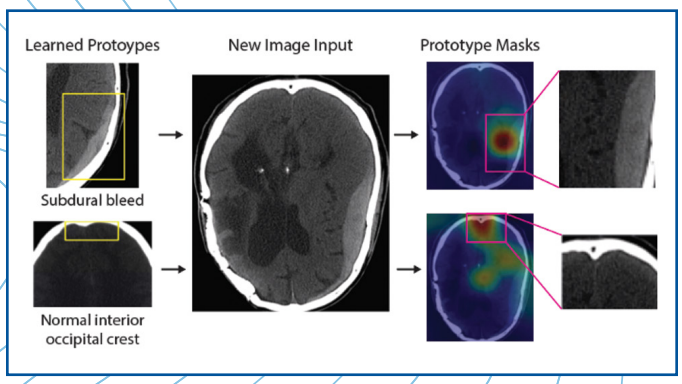


Figure 4. Output from trained ProtoPNet CNN.



Next Steps

The team is preparing to implement and pilot our ICU and inpatient admission model for TBI patients in the Duke Regional Hospital ED. In tandem, we are working to expand our model to predict the additional patient outcomes deemed significant and actionable by our clinical team leaders: close follow-up, readmission, and GCS deterioration. Before integrating real-time image analysis, we will also validate whether brain CT images features automatically derived from our convolutional neural network improve predictive performance. In the future, we also envision delivery of interpretable representations of salient CT image features via our model's dashboard and implementation of a time-aware model that updates its predictions over the course of an entire hospital encounter, thus expanding the model into inpatient and perioperative settings.

Academic Output

Using our DIHI RFA project and preliminary data as a foundation, the team submitted an NIH R01 to the "High-Priority Areas for Research Leveraging EHR and Large-Scale Data" RFA in October 2020. The grant was discussed, and the reviewers were overall enthusiastic, describing the proposal as "ingenious," but we were obliged to resubmit in July 2021 and are awaiting final review.

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IMPLEMENTATION UPDATE
Sepsis Watch

Will Ratliff, MBA



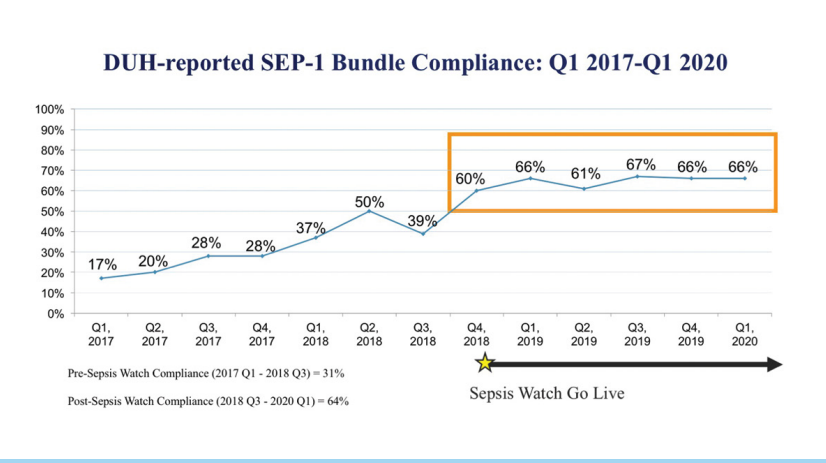
Since the initial go-live of Sepsis Watch on November 5, 2018, Duke Health has applied it in Emergency Department care to predict sepsis earlier and improve timely treatment for Duke patients with sepsis. Sepsis Watch began as an RFA (request for application) proposal submitted to DIHI by Dr. Cara O'Brien in 2016, with the aim of creating an early warning score to improve Duke's detection and care of sepsis patients. Now, the Sepsis Watch solution is an infusion of a machine learning model, an interactive web application to identify and track treatment of septic patients, and a clinical workflow tailored to each of the three Duke Emergency Departments.

Thanks to our front-line clinicians who have incorporated Sepsis Watch into their clinical roles, we have seen substantial improvements in care of sepsis at Duke. Specifically, we have seen a two-fold increase in our SEP-1 bundle compliance, a standard metric of quality of sepsis care that Duke reports quarterly to CMS, at each of Duke's three Emergency Departments (Duke University Hospital, Duke Raleigh Hospital, and Duke Regional Hospital) since the implementation of Sepsis Watch, as compared to the two years prior to its implementation.

Thanks to our front-line clinicians who have incorporated Sepsis Watch into their clinical roles, we have seen substantial improvements in care of sepsis at Duke.

Now, we are working with the Patient Response Program, led by Dr. O'Brien and Dustin Tart, to expand Sepsis Watch into the inpatient setting. We kicked off in June 2021 by extending Sepsis Watch into the general medicine wards at Duke University Hospital, where it is being used by Duke's Patient Response Team (PRT) nurses to identify and track treatment for patients who meet our real-time sepsis definition.

Concurrently, we have been working on Sepsis Watch 2.0, which features an updated machine learning algorithm that is trained to predict sepsis on all admitted Duke patients at any point during their inpatient stay (excluding perioperative settings). We have also developed the Sepsis Watch 2.0 web application, an improved version of the current web app that is streamlined to allow for managing a large volume of patients simultaneously. We are conducting a temporal validation of the new model and user testing of the new web application through the end of this year, and we plan to implement these updates in early 2022.



Lastly, we have nearly completed a detailed examination of Sepsis Watch's pilot period through the end of 2019, with a focus on the solution's impact on clinical outcome metrics. We are thrilled to be part of the evolving science around sepsis, and moreover, we are honored to support the clinicians across Duke's hospitals to combat this disease and improve care for Duke's patients.



A Population Health Strategy for NAFLD Using an E-Consult Platform and NLP

Problem

Non-alcoholic fatty liver disease (NAFLD) is a prevalent disease with variable severity, ranging from simple fat to cirrhosis. It is the most common cause of chronic liver disease in the U.S., affecting approximately 25-30%. Recent estimates suggest two-thirds of U.S. adults are overweight or obese, translating to an estimate of 75 to 100 million U.S. adults with NAFLD. Though the majority of patients with NAFLD have simple steatosis, about a quarter have the progressive subtype non-alcoholic steatohepatitis (NASH), which increases the risk of fibrosis progression to cirrhosis and the development of hepatocellular carcinoma. NASH furthermore independently increases the risk of cardiovascular events and cardiovascular-related mortality.

NAFLD is typically asymptomatic and under recognized, even if advanced to early cirrhosis. Unfortunately, patients with NAFLD typically do not have any symptoms nor knowledge of the disease. Patients are often diagnosed only if they develop significant disease decompensation such as ascites, encephalopathy, variceal bleeding, jaundice, or liver cancer.

Furthermore, current Duke referral practices to Hepatology do not take into account NAFLD severity. At Duke, no guidelines or structured support tools exist to assist in primary care referral of NAFLD to Hepatology, resulting in variable referral practices. Many high-risk NAFLD patients (i.e., NASH and/or advanced fibrosis) fail to receive a timely Hepatology referral, and conversely, many low-risk NAFLD patients are referred to the Hepatology clinic when they could have avoided a subspecialist visit.

TEAM
Yuval Patel, MD, MHS; Andrew Muir, MD; Will Knechtle, MBA, MPH; Michael Gao, MS; Leland Pung, MEng; Sriram Gollapudy; Bradley Hintze, PhD; Marshall Nichols, MS; Mark Sendak, MD, MPP; Suresh Balu, MBA

PROJECT IN BRIEF
Non-alcoholic fatty liver disease (NAFLD) is typically asymptomatic and under-recognized, even if advanced to compensated cirrhosis. No guidelines or structured support tools exist to assist in primary care referral of NAFLD to Hepatology. The team used clinical data and natural language processing of radiology reports to newly identify clinically silent NAFLD patients. We developed a disease-specific e-consult for existing referrals and newly identified patients to deliver high-impact care. As a result, high-risk NAFLD patients are identified and triaged appropriately through a proactive e-consult platform to a liver clinic visit. Low-risk patients can be managed by e-consult alone, reducing unnecessary in-person referrals.

With this project, we therefore sought to:

1. Identify new NAFLD patients within the Duke University Health System (DUHS) using a natural language processing (NLP)-based algorithm, and
2. Use an e-consult platform to better triage care for NAFLD patients by risk assessment.

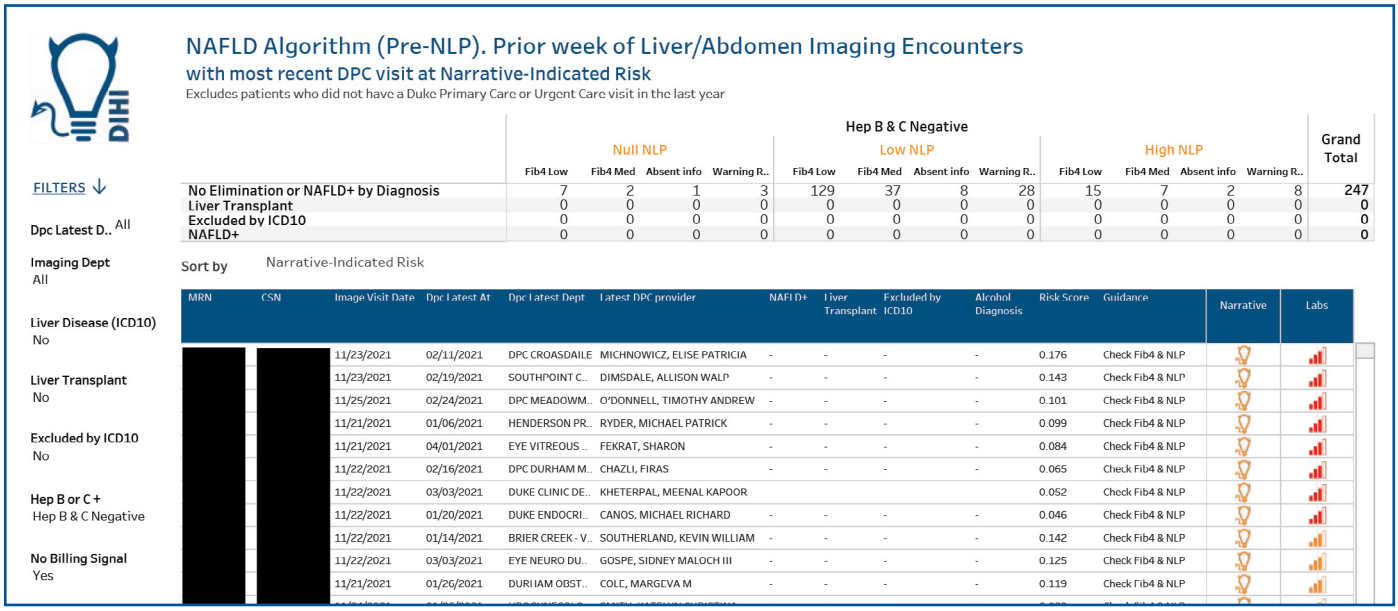
Solution

We developed an algorithm utilizing clinical data and NLP to identify previously unrecognized NAFLD patients within DUHS. Concurrently, we developed a disease-specific e-consult initiative for existing referrals for patients with NAFLD to help minimize in-person consultations for low-risk patients.

Once the program is implemented, every week a hepatologist will review a Tableau dashboard (Figure 1) that will populate with patients who had liver or abdominal images completed in the prior week and also had a Duke Primary Care office or tele-visit in the last year.

An algorithm will identify whether diagnostic or lab results exclude a patient from an NAFLD diagnosis or indicate that they have been diagnosed with NAFLD already. The dashboard will quickly present the patient's image narrative and whether NLP signaled likely NAFLD.

Figure 1. Pilot workflow for low-risk PE patients in the Emergency Department.



NAFLD Algorithm (Pre-NLP). Prior week of Liver/Abdomen Imaging Encounters

with most recent DPC visit at Narrative-Indicated Risk

Excludes patients who did not have a Duke Primary Care or Urgent Care visit in the last year

FILTERS

Dpc Latest D.. All

Imaging Dept All

Liver Disease (ICD10) No

Liver Transplant No

Excluded by ICD10 No

Hep B or C + Hep B & C Negative

No Billing Signal Yes

	Hep B & C Negative												Grand Total
	Null NLP				Low NLP				High NLP				
	Fib4 Low	Fib4 Med	Absent info	Warning R..	Fib4 Low	Fib4 Med	Absent info	Warning R..	Fib4 Low	Fib4 Med	Absent info	Warning R..	
No Elimination or NAFLD+ by Diagnosis	7	2	1	3	129	37	8	28	15	7	2	8	247
Liver Transplant	0	0	0	0	0	0	0	0	0	0	0	0	0
Excluded by ICD10	0	0	0	0	0	0	0	0	0	0	0	0	0
NAFLD+	0	0	0	0	0	0	0	0	0	0	0	0	0

Sort by Narrative-Indicated Risk

MRN	CSN	Image Visit Date	Dpc Latest At	Dpc Latest Dept	Latest DPC provider	NAFLD+	Liver Transplant	Excluded by ICD10	Alcohol Diagnosis	Risk Score	Guidance	Narrative	Labs
[redacted]	[redacted]	11/23/2021	02/11/2021	DPC CROASDAILE	MICHNOWICZ, ELISE PATRICIA	-	-	-	-	0.176	Check Fib4 & NLP		
		11/23/2021	02/19/2021	SOUTHPOINT C..	DIMSDALE, ALLISON WALP	-	-	-	-	0.143	Check Fib4 & NLP		
		11/25/2021	02/24/2021	DPC MEADOWM..	O'DONNELL, TIMOTHY ANDREW	-	-	-	-	0.101	Check Fib4 & NLP		
		11/21/2021	01/06/2021	HENDERSON PR..	RYDER, MICHAEL PATRICK	-	-	-	-	0.099	Check Fib4 & NLP		
		11/21/2021	04/01/2021	EYE VITREOUS ..	FEKRAT, SHARON	-	-	-	-	0.084	Check Fib4 & NLP		
		11/22/2021	02/16/2021	DPC DURHAM M..	CHAZLI, FIRAS	-	-	-	-	0.065	Check Fib4 & NLP		
		11/22/2021	03/03/2021	DUKE CLINIC DE..	KHETERPAL, MEENAL KAPOOR					0.052	Check Fib4 & NLP		
		11/22/2021	01/20/2021	DUKE ENDOCRI..	CANOS, MICHAEL RICHARD	-	-	-	-	0.046	Check Fib4 & NLP		
		11/22/2021	01/14/2021	BRIER CREEK - V..	SOUTHERLAND, KEVIN WILLIAM	-	-	-	-	0.142	Check Fib4 & NLP		
		11/22/2021	03/03/2021	EYE NEURO DU..	GOSPE, SIDNEY MALOCH III	-	-	-	-	0.125	Check Fib4 & NLP		
		11/21/2021	01/26/2021	DURHAM OBST..	COLE, MARGEVA M	-	-	-	-	0.119	Check Fib4 & NLP		

Figure 2. NAFLD algorithm using billing and lab result history to identify NAFLD patients with abdominal images taken between April 2014 and July 2020. A total of 57,106 patients were without adjudicating billing codes, and therefore may have benefited from having their image narratives evaluated with natural language processing.

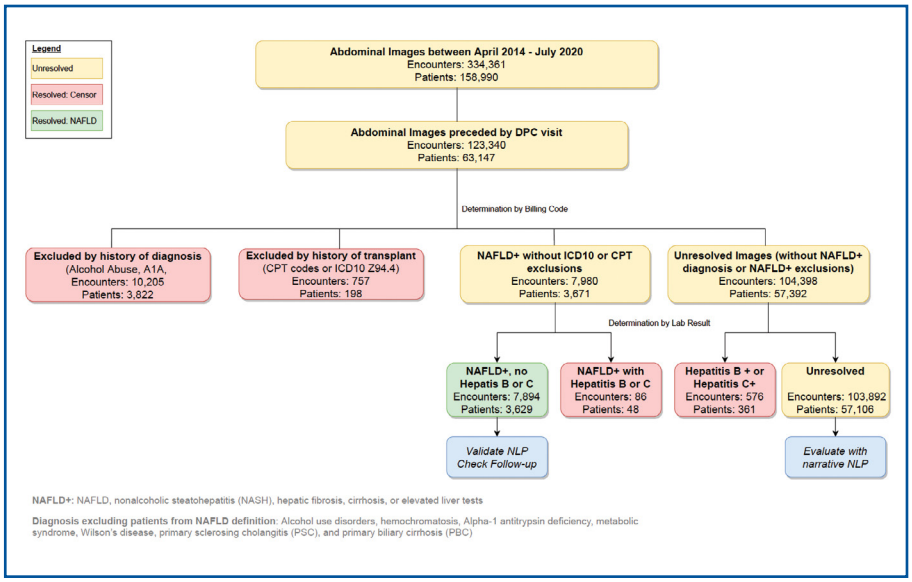
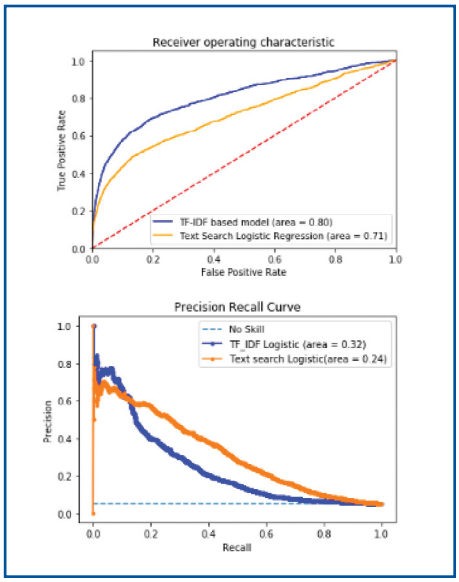


Figure 3. Model statistics: Receiver operating characteristics and precision recall curves.



The latest Fib-4 scores will also be presented per patient for additional decision support to allow for risk assessment. For newly identified patients, we plan to pilot a proactive e-consult initiative targeted at those with suspected advanced disease. We hope this will eventually result in more high-risk NAFLD patients being identified and seen within Duke's liver clinics, and more low-risk NAFLD patients being managed by e-consult alone.

Outcomes

We developed a highly specific clinical data and NLP-driven algorithm to identify new NAFLD patients (Figure 2). On retrospective analysis, the NLP model demonstrated an AUC of 0.80 when identifying patients who had previous billing code for NAFLD (Figure 3). One hundred patients were randomly selected from patients deemed highly likely to have NAFLD (threshold >4.5%), and additional clinical review was performed.

Of these 100 patients, 53% (95% CI: 0.43-0.63) [60.4% female; 60.4% Caucasian, 30.2% Black] were validated as having NAFLD on hepatology review compared to 10% who were billing code positive for NAFLD (95%CI: 0.04-0.15) [60% female; 70% Caucasian, 30% Black].

We are now in the process of piloting the proactive e-consult initiative at partner primary care clinics, focusing on newly identified high-risk NAFLD patients, with the ultimate goal of scaling this effort throughout DUHS.

Next Steps

After our pilot of the proactive e-consult at select primary care clinics, we hope to scale this to more of the DUHS primary care enterprise. We are planning to track how many NAFLD patients are newly identified and triaged to appropriate care, particularly those who are high-risk.

Academic Output

Abstracts have been submitted to the Machine Learning for Healthcare Conference and the AASLD Annual Conference, and manuscripts are planned for the future.

DIHI INNOVATION SCHOLAR PERSPECTIVE

Leland Pung, MEng



When I think about my Duke Institute for Health Innovation (DIHI) scholar experience, what comes to mind are the opportunities and challenges I was given to experience and grow. Through DIHI, I was able to not only learn about the healthcare system, but I was also given the chance to try and implement changes that could truly improve patient care despite the challenge of a global pandemic.

Working on a diverse range of topics, from machine learning for HIV prevention to natural language processing for non-alcoholic fatty liver disease detection, DIHI gave me the opportunity to not only enhance my technical skills but also to improve my soft skills and broad health systems-based knowledge to implement and develop clinical decision support software. Because of DIHI, I gained a far deeper understanding of how a large academic health system operates, and I learned the important skills and understanding needed to navigate complex challenges moving forward. I know I will use the skills DIHI taught me far into my future as a clinician.

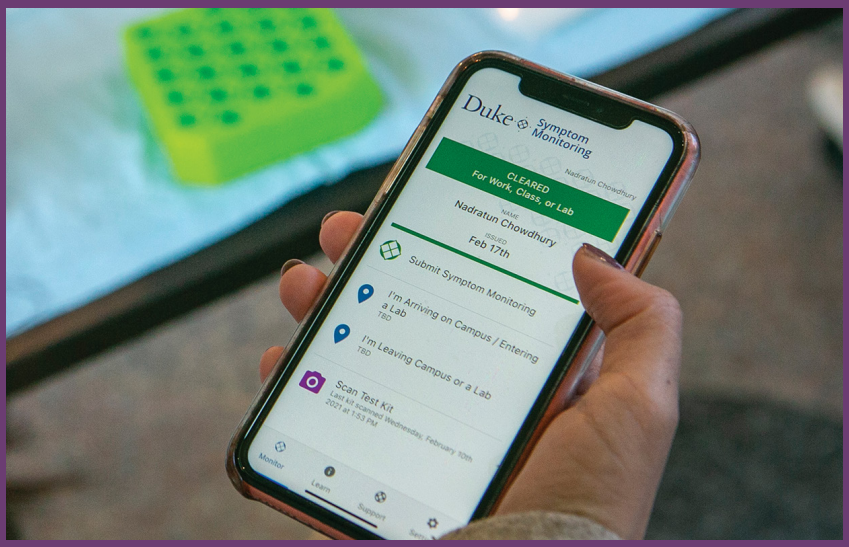
IMPLEMENTATION UPDATE
SymMon

Mike Revoir and Matt Gardner, BS





COVID-19 still loomed large as the fall 2020 semester approached. As Duke students, faculty, and staff looked forward to reengaging in campus activities, the need arose for a technology solution focused on early detection of COVID-19 symptoms and tracking potential cases. DIHI partnered with the Duke Office of Information Technology (OIT) to build a mobile app platform, named SymMon, with the goal of it being available in app stores when students returned to campus—less than four weeks from project initiation.



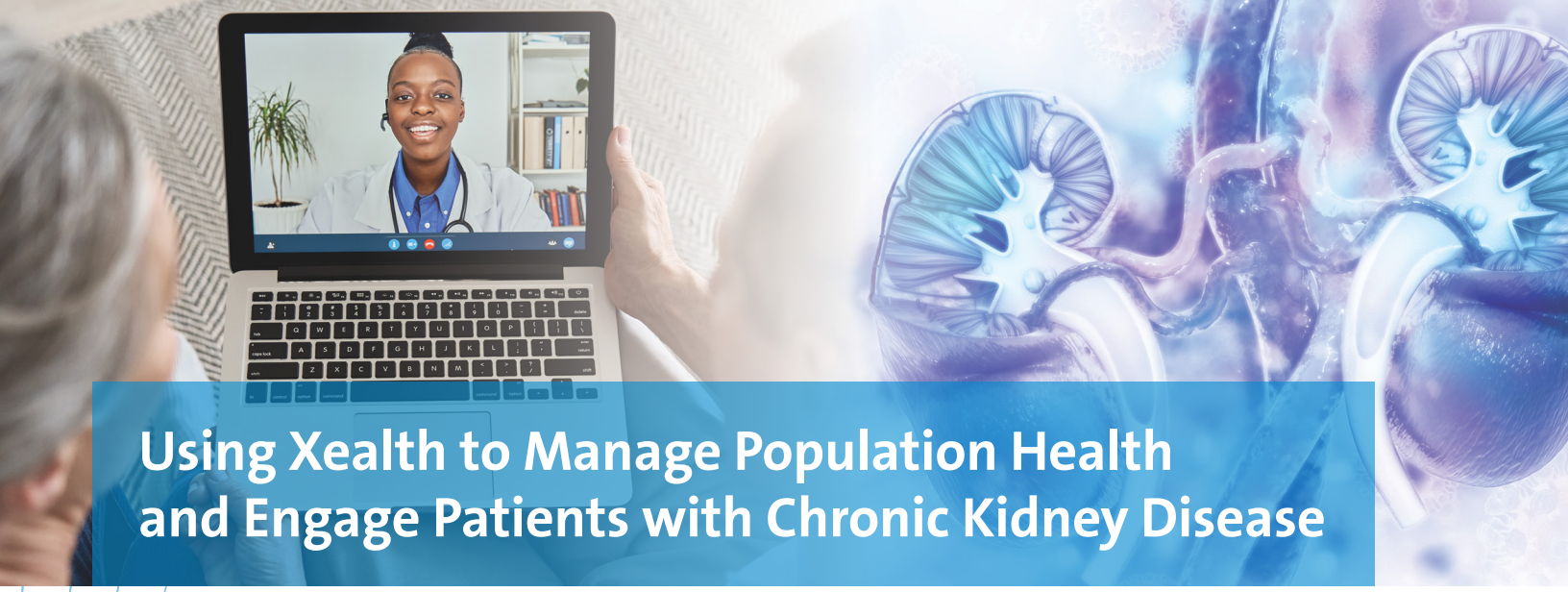
With over 34,000 users and 27 releases to date, the Duke Symptom Monitoring App (SymMon) has continued to play a valuable role in Duke's response to the COVID-19 pandemic. Although it initially focused on allowing users to report their COVID-19 related symptoms, SymMon has expanded to now support scanning test kits; it provides users with insights about their DukeCard and the review status of their reported symptoms and exposures. This project has continued to be a successful partnership with Duke OIT and will continue to evolve to meet the needs of the University.

DATA SCIENCE STUDENT EXPERIENCE

Linda Tang



I am a senior at Duke studying biology and statistics with a minor in chemistry. I am interested in working in the medical field, and I continue to explore the application of data science in healthcare. I am currently working on DIHI's Pediatric Sepsis project, in which we use machine learning methods to detect pediatric sepsis in advance. In my free time, I enjoy playing the guitar and exploring food places in Durham.



Using Xealth to Manage Population Health and Engage Patients with Chronic Kidney Disease

Problem

Under value-based care, we must ensure that every patient receives the right care at the right time and in the right setting. Both patients and the health system alike suffer when unnecessary care is given (waste) and when needed care is foregone (worsened health). We ought to provide exactly the level of care the patient needs—no more and no less.

The Duke e-Consultation program, which was also initially funded by the Duke Institute for Health Innovation (DIHI), expanded the scope of primary care and improved efficiency. eConsults provide Primary Care Providers (PCPs) with virtual specialty support and assistance in determining the necessity of a referral.[1] Through this program, PCPs have been empowered to care for more complicated patients. Many patients who previously would have needed specialty referral are now treated "in place" in primary care. The E-Consultation program improved provider-to-provider communication and increased the availability of specialist appointments for higher-risk patients.[2]

However, two unresolved problems remained. First, the E-Consultation program did not address under-treatment, in which a patient received less care than was needed. Chronic kidney disease (CKD) exemplified this problem. Abundant literature demonstrated the benefits of early detection, treatment, and specialty referral in CKD.[3] Yet CKD was frequently under-recognized and under-treated in primary care.[4] The majority of patients with CKD were unaware they had the illness.

TEAM

Blake Cameron, MD; Patti Ephraim, MPH; Tara Kinard, RN, MSN, MBA; David Claxton, MMCi; Allyson Alexander; Lydia Smith; Ebony Boulware, MD, MPH; Will Knechtle, MBA, MPH

PROJECT IN BRIEF

Many chronic health conditions are under-recognized and under-treated, and patients suffer as a result. Chronic kidney disease (CKD) is a prototypical example. Duke Health has several programs to improve treatment of chronic disease in primary care, including e-consultation, clinical decision support, and digital patient education, but the optimal combination of these tools is unknown. Our team piloted a CKD population health management intervention in Duke Nephrology and Duke Primary Care that tests novel combinations of clinical decision support, e-consultation, and patient-facing digital education (through Xealth). The proactive management of CKD helps prevent CKD progression, and lessons learned inform population health management activities more broadly.

A variety of clinical decision support alerts had been used to nudge providers to improve diagnosis. No real-world data existed to show the effectiveness of different kinds of alerts, and Duke lacked technical methodology to perform randomized A/B testing of clinical alerts as part of a quality improvement project. Second, the E-Consultation program did not provide patient education. When a specialty visit was avoided, the patient lost the benefit of disease-specific counseling from the specialist. Existing health education resources available in primary care were overly generic and were not appropriately tailored to an individual patient's condition or educational needs.

Solution

We needed a scalable, population-based approach to CKD that ensured timely recognition and treatment and also enabled patients to better manage their illness. We needed to compare different approaches to alerting providers, with the goals of improving patient engagement and accelerating development of similar capabilities for many other chronic diseases and conditions. We postulated that proactive identification of CKD would result in more appropriate specialty referrals and improved patient engagement.

At three Duke Primary Clinic sites, we piloted a CKD population health management intervention that utilized provider decision support and patient-facing Duke MyChart and Xealth digital education portals to guide appropriate specialty consultation and deliver tailored patient educational content. We obtained Duke Institutional Review Board exemption.

The intervention consisted of three components:

1. The first component made the Kidney Failure Risk Equation (KFRE) score and interpretive guidance visible to all Duke providers in the Epic Storyboard banner. The KFRE estimates the likelihood that a patient will develop kidney failure in the next two to five years.

2. The second component was a best practice advisory (BPA) that we deployed at three Duke Primary Care sites: Pickett Road, South Durham, and Triangle Family Practice. A BPA is an interactive alert in a patient's chart triggered by specific clinical criteria; in this case, the presence of high-risk CKD as defined by a high KFRE score.

3. The third component was the Xealth digital education platform. CKD education materials ("Living with Kidney Disease" and "PREPARED") developed by Dr. Ebony Boulware, Chief of Duke General Internal Medicine, were formatted digitally (including video) and tailored for Xealth distribution. The KFRE score triggered the BPA. The BPA in turn triggered distribution of educational content as well as prompted providers to discuss CKD with the patients and/or suggested E-Consultation.

We implemented the intervention using a cluster-randomized design at the individual provider level. Each provider was randomized to one of three groups representing increasing intensity of decision support. Patients of all three provider groups received CKD educational content automatically via Xealth. Providers in group (A) received no visible BPA alerts. Providers in group (B) received a BPA alert, prompting them to encourage the patient to view the digital educational content. Providers in group (C) received a BPA alert similar to group B that additionally prompted them to consider ordering nephrology E-Consultation if the patient was not already established with nephrology care. In both groups (B) and (C), providers were asked to add CKD to the problem list in the patient's chart if not already done.

The implementation process was monitored through internal dashboards and external Xealth platform applications. The internal Nephrology Chronic Kidney Disease BPA Dashboard was created by DIHI and maintained by Duke University Health System (DUHS) Performance Services.

Outcomes

We developed two new technological processes for use in Duke MyChart. First, we created a new method for performing A/B testing of clinical alerts randomized at the provider level. Second, we created a method for applying complex logic that incorporated risk prediction scores and other clinical data to trigger automated delivery of Xealth digital assets.

Between November 2020 and April 2020, 599 BPA alerts were displayed to providers and 270 (45%) were acted upon. Of those, 176 patients received educational content via Xealth. Patients opened half (53%) of the emails sent to them, and 10% of patients opened the Xealth materials in the patient portal. Patient engagement with Xealth content in this project was typical compared to typical engagement rates across DUHS and was uniform across the different groups of provider alerts.

The BPAs that garnered the highest rate of provider action were those that were most specific in their requests: prompting the addition of CKD to the problem list when not already present, and/or soliciting a Nephrology consultation for patients not already established.

Continues on next page >

A Nephrology eConsult was ordered for 85% of the patients for whom providers were prompted by the BPA, significantly closing the gap between guideline-recommended referrals and historical referral performance. The project funded the creation of animated patient education videos that were adapted from Dr. Boulware's "All the Facts about Kidney Disease" handout.

Academic Output

This project extended two highly successful programs previously sponsored by DIHI. The Duke Connected Care Chronic Kidney Disease Improvement Project (DIHI RFA 2015) established the Chronic Kidney Disease Registry, including the Kidney Failure Risk Equation calculation. The CKD Virtual Medical Neighborhood Project (DIHI RFA 2016) established the Nephrology E-Consultation program.

The technological and programmatic infrastructure that was established in this current project is now being leveraged to support two multi-center clinical trials, both led by Dr. Boulware as principal investigator, totaling $15 million: NIDDK's 'Health system outreach to eliminate disparities in living kidney transplants' and PCORI's 'Helping Patients Achieve Kidney Transplants through Health System Change.'

Next Steps

We will automatically deliver CKD educational content to all eligible patients in Duke primary care. We will show only the most actionable BPA alerts to providers. We will carry forward lessons learned to proactive kidney transplant referral from Nephrology clinic as part of the clinical trials discussed above. We will share the methodology for BPA randomization with the EHR Provider Optimization Council to enable rigorous evaluation of future decision support tools.

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IMPLEMENTATION UPDATE
Chest Pain Assessment Tool

Mike Revoir



The Duke Institute for Health Innovation developed the Chest Pain Assessment Tool (CPAT) as a web-based app that computerized two algorithms into one clinical decision support tool, a high-sensitivity troponin (hsTn) algorithm and HEART algorithm (patient History, ECG abnormalities, Age, any Risk factors present, and Troponin measurement), and then presented summative clinical care and disposition recommendations based on the combined results. While the app can be accessed via a standard browser URL, we placed multiple links within Maestro Care to launch the app directly from within a patient's chart and optimize clinician convenience.

Since launching CPAT, Duke Health has continued to apply the high-sensitivity troponin disposition algorithm daily to dozens of encounters within the emergency department. We are currently working to expand this accelerated diagnostic protocol to other institutions through licensing, and we have established an API and demo application incorporating the HEART score and disposition algorithm to produce recommendations.



DIHI PERSPECTIVE

Expanding DIHI's Impact through External Data Science Partnerships

Mark Sendak, MD, MPP

The idea that "software is eating the world" was popularized by venture capital firm Andreesen Horowitz. The ability of software to rapidly scale impact truly is remarkable, and when it's something you have witnessed, it can be hard to proceed with caution.

Witnessing software scale is part of what motivated me to pursue a career in health innovation. For two years as a medical student, I was building tools to support an adult primary care clinic that served 5,000 adults. The next year, I joined the Duke Institute for Health Innovation (DIHI) and built tools to support an accountable care organization that served over 50,000 adults per year. A few years after that, our team built a sepsis monitoring platform that reaches every adult presenting to any Duke Health emergency department, which is well over 100,000 adults per year.

The technologies and workflows developed through DIHI projects are now embedded into clinical operations across the Duke University Health System (DUHS). New projects continue to serve as rich opportunities to build new capabilities, reach new populations, and solve new problems. But while we continue to create and pursue opportunities for impact within DUHS, we are often left wondering: What are the opportunities for impact beyond our organization? If we validated software that solves a problem for us, how well would this software work in other settings?

Over the last few years, we have encountered leaders near and far who ask similar questions. We meet with innovators and technologists who have their own software solutions that they are looking to further validate. On the other hand, we meet with clinical and operational leaders who want to learn more about technologies we built internally to DUHS. While these conversations each represent exciting opportunities to create value, our experience working with real-world health data has led us to proceed with caution. Health data is not interoperable, every system captures data with its own set of nuances, and the structure of health data is constantly changing.

Thankfully, the time and effort we invested over the last few years in refining infrastructure and best practices to work with real-world health data are starting to pay off. The DIHI data pipeline, model and data monitoring tools, and data quality reports are just a few examples of technologies we've built that allow us to more quickly execute internal projects. And these tools are just as useful for external partnerships as they are for internal projects. We're now able to enter new environments and rapidly assess data and infrastructure to ensure that software validations can be carried out smoothly. While each external partnership requires special attention and diligence, we have refined the process to engage more broadly.

We are excited to share that a large number of new partnerships have been cultivated in 2020-2021. COVID-19 certainly helped organizations embrace that they could not tackle healthcare's big problems alone. We also find a great deal of enthusiasm to collaborate on product development and validation efforts between health systems. For too long, data science and software development were activities conducted solely in private industry. We hope that our partnerships build capabilities and confidence across health systems to develop and integrate new technologies.

Whether you're a healthcare leader thinking of evaluating something we've built at DIHI or whether you're an innovator building your own solution, please don't hesitate to reach out. We're always looking to expand the impact of well-validated software, and we'd love to be a part of your innovation journey.



Using a Mortality Risk Predictor Model to Improve Advance Care Planning for Patients in the Hospital by Means of a Transitions of Care Toolkit

Problem

Many patients admitted to the hospital are seriously ill and at risk of dying. Improving goals of care discussions in the hospital requires providers to be able to accurately identify patients who are at risk of mortality. In addition, the inpatient providers must be able to communicate to their patients the severity of their illness so that they may have realistic expectations and be able to make informed medical decisions.[1] However, evidence suggests that physicians perform poorly in predicting prognosis and life expectancy for patients.[1,2] Hence, goals of care discussions between physicians and patients do not occur consistently; furthermore, the content, detail, documentation, and timing of these discussions are variable. Seriously ill patients are, thus, at an increasing risk of being exposed to potentially unwanted interventions at their end of life.[3,4]

These observations from the literature are also true at Duke University Health System (DUHS). Multiple physician reviewers on the mortality OnBase tool have identified having earlier goals-of-care discussions as an opportunity to improve care for patients who die in the hospital. Improving end of life care delivery and advance planning, including improving hospice referral for seriously ill patients, has also been identified as a strategic goal for DUHS.

Solution

In 2018-2019 the Duke Institute for Health Innovation (DIHI) developed a model by using electronic medical record data to estimate the probability that a patient will die during a hospital stay as well as 30 days after discharge.

TEAM

Amanda Bisset, MD; Aparna Kamath, MD, MS; Lalit Verma, MD; Trig Brown, MD, MPH; Paula McKenzie, RN; Merrille Asuncion; Will Knechtle, MBA, MPH; Michael Gao, MS

PROJECT IN BRIEF

We used a mortality risk predictor model to identify patients who were at high risk for 30-day mortality and who were admitted to the hospitalist service at Duke Regional Hospital. We then discussed the identified patients at the Just in Time Palliative Care Huddle. During that discussion, the palliative care team identified any potential needs for the patient while our coordinator reached out to the patient's primary team to inform them of their patient's 30-day risk of death as identified by the tool and to offer the appropriate resources. Those resources were part of a Transitions of Care Toolkit we developed. We then followed those patients and collected data on the resources used and the outcome of the hospital stay.

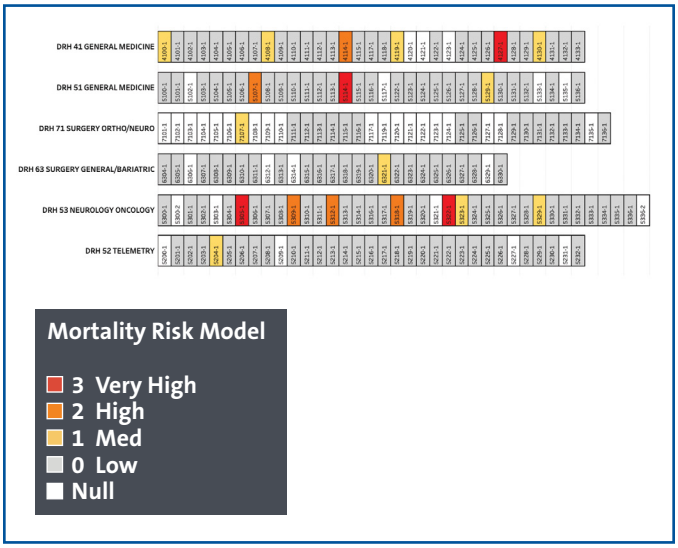
We used this mortality risk predictor model to identify patients who were admitted to the hospitalist service at Duke Regional Hospital with a high 30-day risk of mortality. Once identified, we informed physicians taking care of those patients about the high risk of mortality and offered them a Transition of Care Toolkit (TOCTK). The TOCTK was authored by a multidisciplinary team and included tools and resources for physicians to improve goals of care and end of life discussions with their patients. It also included personalized tools for the patient, geared toward improving their quality of life and supporting them as needed after discharge.

Outcomes

In the summer of 2020, DIHI created a specialized view of its HealthGuard dashboard. This dashboard focused on ten Duke Regional Hospital General Medicine floors, and furthermore it used adjusted model thresholds that accounted for the volume of 'Very High' and 'High' risk patients we believed we could review within our Just in Time Palliative Care Huddle and respond to with Advanced Care Planning (Figure 1). By October 2020, we had hired Merrille Asuncion as a part-time project manager, and she began reviewing the dashboard and adding patients to huddle discussions. We found that 60 of 737 (8%) of patients discussed in the daily huddles between Oct 12, 2020 and February 26, 2021 would not have been discussed if it were not for the mortality model and HealthGuard dashboard. The huddle team agreed that 83% of these 60 newly-identified patients merited the further attention recommended:

Of the patients who were part of the intervention cohort of 60 patients:
a) 16 (37%) had ACP documentation
b) 9 (15%) had code status changes
c) 25 (42%) had family discussions

Figure 1. A view of Duke Raleigh Hospital general medicine hospital beds presenting the 30-day Mortality Risk, according to the DIHI HealthGuard mortality model. Updated every 15 minutes on a Tableau dashboard.



After adjustment, we find that patients who were identified via the model and included in the palliative care huddles had:

- A 12% increase in ACP note documentation (2% → 14%)
- No significant improvement in 30-day readmissions
- A 7% increase in discharge to hospice (3.5% → 10.7%)
- A 26% increase in code status changes (4% → 30%)

(Note that the rates in parentheses are adjusted rates (balanced by propensity of receiving treatment)).

During the post-discharge follow up survey, we had several comments from patients and their families who felt like the services they received with the palliative care team were helpful and appreciated. Surveys of providers increased awareness for .gmacp dot phrase from 67% to 100%. The survey also found that many providers still feel like they do not have enough time for the goals of care discussions they would otherwise like to have or complement (of note, the pre-intervention survey had 33 responses whereas the post intervention survey had 15).

Next Steps

The project manager, Merrille, is continuing her work. She is using the same workflow but is no longer collecting data at the same level that was needed when researching the process. By June 2022, we aim to submit our methods and results for publication.

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DIHI PERSPECTIVE

Preventing Deterioration through Data Science

Will Ratliff, MBA and Michael Gao, MS

Why do patients deteriorate in the hospital? The clinical answer to this question is complex, as the individual causes of deterioration are an evolving science and often co-occur in practice. Considering the numerous interventions available to treat each type of deterioration individually, it is challenging to pinpoint a single clinical driver of deterioration and appropriate intervention in real-time.

Dr. Cara O'Brien once shared a memorable parallel to the poker game Texas Hold'em to illustrate the need for increased visibility into real-time deterioration. As the clinician, you begin with limited information on a deteriorating patient (your two cards), and you have an initial decision on the type and size of intervention (your initial wager). As you learn more about the patient by observing vital signs, collecting labs, administering medications, etc. (the dealer reveals the flop, then the turn, then the river), the type of deterioration (your hand) and the appropriateness of your intervention decisions (your wagers) become clear. Except, Dr. O'Brien pointed out, the stakes are your patients' lives. At Duke, we have the opportunity to "change the game" by learning from the past and applying that learning to identify deteriorating patients earlier so that our clinical experts can intervene. The first step is answering the question: What is deterioration?

We can begin to define deterioration by labeling observable "ground truth" events in retrospective data, such as in-hospital deaths or unanticipated patient transfers from intermediate- or step down-level care to intensive care units (ICUs). These labels have low missingness and low ambiguity (for ICU transfers, this is true after some thoughtful logic and data processing). With these labeled events, we get two crucial insights related to the "Why deterioration?" question.

First, we get a time window and associated clinical data leading up to the deterioration event, which we can use to identify data trends and develop models to predict deterioration.

However, the potential to unlock meaningful signals of imminent deterioration depends on the ability to access and harmonize the data such that missingness and noise are mitigated. Information nestled in clinical notes and procedure-influenced perioperative data provide two examples of this challenge. Moreover, the rate of retrospective data points available to train a model can result in a tradeoff between the frequency and accuracy of the model's "real-time" predictions. For example, let's say you are training a model on patient vitals data with the goal of generating hourly predictions of a patient's need for ICU transfer within the subsequent 12-hour window. But, vitals data are only documented every four hours.

As a result, your model is expected to give a different answer ("not needed" at 13 hours before ICU transfer, "yes needed" at 12 hours before ICU transfer), yet the vitals data it is using looks exactly the same between those two hours about half the time. Given the various care pathways, documentation methods, and data storage locations of hospitalized patients, there is still progress to be made to achieve a holistic data profile with a high degree of time resolution for each inpatient encounter. We see this as an enormous opportunity and continue to prioritize helping in this collaborative effort across Duke Health.

The second insight we get from these "ground truth" deterioration labels is a means to evaluate clinical indicators of deterioration, such as respiratory failure and end organ dysfunction. The definitions of these clinical indicators can be more nuanced and are certainly more complicated to ascertain from raw electronic health record data. For instance, while hypotension is generally agreed upon as blood pressure below 90/60 millimeters mercury, the manifestation of this legitimate clinical condition in the data is confounded by blood pressure cuff malfunctions, patient position changes, erroneous data entries, etc. Thus, clinical care providers must make a decision about the inclusion criteria to identify true, sustained hypotension in hospitalized patients.

Working with our clinical collaborators, we developed a digital phenotype of hypotension as either (1) two systolic blood pressures below 90 within a six-hour timeframe, or (2) two mean arterial pressures below 65 within a six-hour timeframe. Thanks to the work completed to develop the "ground truth" deterioration labels, we were able to refine this definition as a marker of clinical deterioration by evaluating rates of ICU transfer and in-hospital mortality in patients who met one version of the definition versus another. For the definition we settled on, we observed a 100% increase in unanticipated ICU transfers and a nearly 400% increase in in-hospital mortality for adult patients who met the definition, as compared to all adult patients.

We can combine digital phenotypes like the hypotension example with others to construct and iterate on real-time definitions of deterioration that include such symptoms, such as sepsis or cardiogenic shock. While we continue to refine and train predictive models on these clinical labels, we are also working with our clinical leads at Duke Health to use these labels in real-time to identify patients at risk of deterioration earlier. Our hope is to transform "Why deterioration?" from a question into an observable real-time signal so that our clinicians can intervene on patients before they deteriorate.

IMPLEMENTATION UPDATE
Pandemic Response Network

Mark Sendak, MD, MPP



Between April 2020 and April 2021, over 10,000 people participated in the COVID-19 Community Health Watch program that the Duke Institute for Health Innovation (DIHI) launched with partners across Duke Health. (Duke Community Health Watch is a member of the Pandemic Response Network, a group of organizations working together to monitor symptom escalation throughout the U.S. in order to track possible new outbreaks of COVID-19). The program provided twice-daily symptom checks with text and email reminders, coupled with nurse triage follow-up for anyone who reported severe symptoms. The vast majority of participants lived in Durham and surrounding areas. Many participants repeatedly used the service during the pandemic.

The Community Health Watch program was closed in April 2021, as the COVID-19 vaccine became more available and the need for symptom monitoring became less widespread. Despite success with rapidly standing up remote monitoring and providing population health support to the broad community, Community Health Watch faced two major challenges. Both challenges were associated with the low uptake of the program by historically marginalized communities, who were disproportionately impacted by the COVID-19 pandemic.

First, many Black and Latinx individuals were not eager to participate in clinical research. The indefinite storage and use of private data for research contributes to a feeling of discomfort for many individuals in historically marginalized populations, and significant effort is required to build trust. Second, relying on MyChart as an engagement channel systematically excludes significant portions of Black and Latinx community members. MyChart was not available in Spanish, and uptake of MyChart is particularly low among Black and Latinx community members. Participant enrollment was at its highest during MyChart outreach to Duke Health patients, but over 90% of enrollees were non-Hispanic and White.

Through the Pandemic Response Network, DIHI and Duke Health built relationships with community-based organizations and community leaders that will inform health innovations for years to come.

Through the Pandemic Response Network, DIHI and Duke Health built relationships with community-based organizations and community leaders that will inform health innovations for years to come. The 2022 RFA included health equity and community engagement as strategic priorities for the first time ever, and we are excited to incorporate our lessons from PRN into future efforts. Our team is dedicated to making space for addressing the needs and concerns of historically marginalized communities in our health innovation work.



DIHI PERSPECTIVE

Walls Up before Hospital at Home

Will Knechtle, MBA, MPH

He watched floor tiles reflect the flickering hallway lights and his glass door translucently mirror dark blue computer monitors. He listened to the sounds of the hospital, which woke him frequently at night. The lonely bedridden man had been away from home for six months, sleeping in hospital beds for weeks in a row, his mind racing in the night. Were his kids going to grow up without a father? Was he going to die from a complication? Was it going to be from an all-too-common hospital-acquired infection? He realized how cold, lonely, and anxiety-provoking the hospital could be, especially at night. He yearned for the comfort of his own bed and the presence of his family. This was David Zaas, then president of Duke Raleigh Hospital, and the time was well before COVID-19.[1] When he gratefully returned to work, he began exploring what acute inpatient care could be done outside the walls of the hospital. Between March 2020 and March 2021, he and Dr. Vidhya Aroumougame proposed and launched a "Hospital at Home" pilot with the Duke Institute for Health Innovation (DIHI).

On April 16, 2021, I joined Dr. Aroumougame's hospitalist visit to the home of Marilyn Moore for her discharge from Duke Hospital at Home care. Marilyn was not the one packing up to leave, but rather the two infusion nurses and two doctors who had visited that day. She was able to comfortably receive treatments on her couch with her daughter, Linda Bustillos, beside her. After her mother's discharge was complete, Linda explained, "The more we can keep the routines the same, the better the outcome. She likes her home; she's comfortable here. This program has been wonderful for her. The whole experience has enabled me to get involved in my mom's care in a totally different way."

The intent of the pilot was to demonstrate that Duke could not only provide rehabilitation, triage, and diagnostic procedures in the home setting, but could also provide safe and high-quality inpatient-like care for select serious illnesses.

And we did. Our team built an infrastructure within Duke capable of meeting all requirements for approval and payment from the Centers for Medicare & Medicaid Services (CMS) Acute Hospital Care at Home program.

Behind the scenes, the 13 months between March 2020 and April 2021 were incredibly laborious. Workflows were mapped and scripted for 10 service areas. Patient education materials were developed with the DUHS Patient Education Governance Council and distributed. In-home and hospital floor nursing competencies were parsed and recombined for Hospital at Home. Two days of technical testing and nurse training was organized and provided. Patient consent documentation was finalized and approved. Medical materials were adjudicated, ordered, and stocked. A novel mobile food delivery process was developed with Duke Raleigh Hospital food services.

A new inpatient unit was configured in Epic for data continuity within the IT infrastructure. A live Tableau dashboard was created to filter Emergency Department patients and new inpatients for primary enrollment criteria (zip code, insurer, hospital service, visit reason) and to alert hospitalists. A revenue management structure was created and a cost center assigned. Finally, Duke Raleigh executive leadership approved protocols, which were submitted and approved through the CMS waiver application—providing the ultimate financial and regulatory support.

By April 2021, we had treated a 'Hospital at Home' patient and developed an 'Acute Hospital Care at Home' infrastructure that met CMS requirements. Through parallel "Enhanced Home Health for COVID-19 (EHHC)" efforts at another health system hospital, Duke Health rehabilitated COVID-19 patients at home through relationships with Duke HomeCare and daily tele-health infrastructure use by hospitalists (Figure 1).

However, only one patient was treated through the DIHI inpatient pilot, and the EHHC efforts wound down as COVID-19 hospitalizations became less threatening to capacity limits. We can learn why these efforts struggled and how to move forward by reviewing four major barriers: financial-regulatory, technological, cultural, and demographic.

Financial and regulatory barriers were deeply intertwined. While payment for extramural medical care and services has long been available, regulatory and billing systems pair site-of-care requirements with service-level requirements. A multitude of inpatient-level hospital services were not certified within the home setting and therefore not reimbursable. Typically, a team could solve this problem through IRB-approved research funding, but that innovation pathway is designed to test single new drugs or procedures or incremental quality improvement. Hospital at Home required multiple overlapping tests and procedures over several consecutive days—all familiar procedures, but all in a new location. Administrators asserted that we could not pay for an entire patient stay, such as this, through research funding. We were stuck. Hospital at Home had to be tested to become certified, could not be tested without payment, and could not be financed without certification.

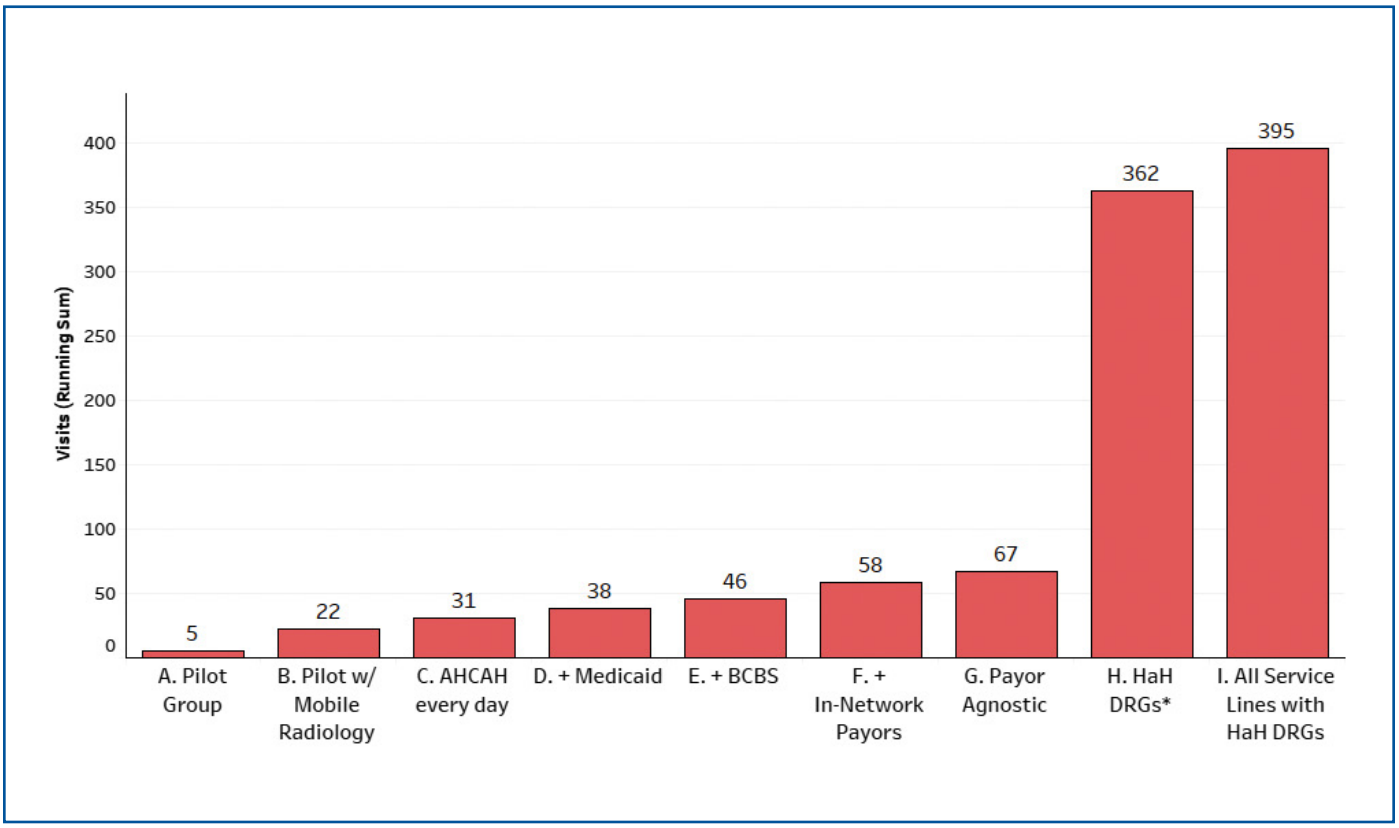
Thankfully, in November 2020 we were pulled out of this quagmire when CMS's Acute Hospital Care at Home waiver promised both certification and payment. Hospital at Home efforts at Duke and institutions across the country are now dependent on this waiver. To enable care delivery innovation ahead of payment reforms, health systems must develop streamlined processes for approving new, complex care designs.

The second and most time-consuming barrier we faced was technological. The primary technological barrier was that the electronic health record (EHR) design rigidly tied financial and legal codes to inpatient and outpatient care sites, with no provision for this hybrid system of care delivery. This barrier was heightened by reluctance to address technology challenges in parallel, rather than in sequence, with financial and regulatory challenges. The secondary technological barrier was the fear that hospitalists could not provide safe or certifiable care without comprehensive EHR documentation. Fortunately, in the wake of the COVID-19 emergency, experienced peers such as Brigham and Women's, Johns Hopkins, and Mount Sinai began providing free webinars and resources,[2] including technical templates and assurance to Duke Health Technology Solutions (DHTS) teams.

Figure 1. Comparing Acute Hospital Care at Home (AHCAH) to Enhanced Home Health COVID Care (EHHCC).

	DUKE RALEIGH HOSPITAL (DRaH) AHCAH	EHHCC
CMS	With AHCAH Waiver	Without waiver or insurer agreement
Encounter class	Inpatient	Telehealth or other outpatient
Patient conditions	Asthma, COPD, PNA, UTI, Cellulitis, AHF	Low-risk COVID-19
Physician interaction	Hospitalist in-person	Hospitalist virtual
Nurse interaction	2 per day, Duke HomeCare and Hospice (DHCH)	2 per day, Duke HomeCare and Hospice (DHCH)
Patient entry point	DRaH ED and General Medicine Floors	Duke University Hospital (DUH) General Medicine
Billing mechanism	Inpatient by DRG Non-DRaH services billed to DRaH	Outpatient through DHCH, supported by DUH
Provider platform	New inpatient AHCAH Epic department Hospitalist cellphones	DHCH non-Epic platform
Patient distance limit	<=10 miles, local Raleigh zip codes	DHHC range, greater Durham focus
Pharmacy	Duke Raleigh Central Pharmacy, documenting in Medical Administration Record, Duke Infusion delivery	Outpatient Pharmacy, Duke Infusion

Figure 2. Eligible DRaH patient volume according to enrollment criteria, according to FY21 inpatient data. Always excludes visits to the OR or ICU, visits needing CT, MRI, or PET imaging; visits not discharged to Home or Home Health; patients <18 years old; residents living >10 miles away; and length of stay >14 days. Analysis with Gina Valo, MMCi



We learned to prevent front-line clinicians from getting stuck in the "EHR trap."[3] Rather than let EHR documentation define clinical workflows, we needed novel clinical care workflows to define EHR documentation. The third and most nebulous barrier was cultural. When you read about DIHI projects and engagement, you may notice how deeply we believe in engaging stakeholders and building buy-in before piloting and, especially, diffusing innovation. This project was unique in its close engagement of over 150 Duke employees across multiple disciplines. When chiefs and presidents directed decisions, Duke Hospital at Home made quick strides forward. However, we also needed mid-level managers to independently direct decisions that determined technical details and engaged front-line staff. Design of specific workflows was endangered by a "buy-in bazaar"[4] and slowed by consensus-based decision making.

I benefited from assigning decision-making power to key persons and clearly communicating who those persons were. These persons had to commit to moving meeting agendas and action items forward without unanimous agreement. With any innovation, there is fear of the new and unknown. Especially when short-term financial incentives are absent, as they were in this pilot, confidence and ownership by health system senior leaders mitigated concerns among mid-level managers. Improving healthcare often requires leaders to support care delivery innovation despite occasional fear or dissent. We learned that Hospital at Home is feasible but relies entirely on committed executive leaders who champion the vision and purpose of the program.

The fourth barrier was overly narrow patient eligibility criteria. The one patient enrolled in the pilot between April and August was a happy example but presented us with a discouraging singularity.

Most eligibility criteria were in place for the protection of patients and so that the standard of care merited "Acute Hospital Care at Home" reimbursement from CMS. For example, geographical limits ensured that patients could be quickly transferred to an intensive care unit or receive an in-person visit. Enrolled patients required a home with reliable electricity and connections for remote monitoring device support. Furthermore, the patient needed care for at least two consecutive nights with frequent medical intervention—otherwise they could be discharged or followed-up on with ambulatory home health nurse visits. Fortunately, this barrier is the most easily mendable: we could change several other eligibility criteria. Physicians were reluctant to enroll patients on a Friday, Saturday, or Sunday because staffing was lower on those days, so communicating with people when transferring patients to the home would have been more difficult.

Left to Right: Marilyn Moore; Marie Witte, MD; Justin Dixon, RN



Nevertheless, improving staffing and communication could allow them to admit patients during those days and thus could increase patient volume by 41% (according to admission trends of similar patients in 2019, Figure 2). Medicaid patients were excluded due to provider perceptions about medical and home conditions, but including them could increase volume by another 23%. After the other demographic inclusions, gains from inclusion of patients from our largest private insurer would increase eligibility by 21%. We learned that a viable Hospital at Home program is within grasp for most health systems, if care providers are granted the time and leadership support to treat the appropriate patients.

We are proud to have pioneered the first Hospital at Home effort among academic medical centers in North Carolina (we applaud Atrium Health[5]), but we have a long way to go. National and local healthcare systems are moving forward more quickly than Duke Health. Duke has been supporting care redesign and is a leader in research-based quality improvement, but we must catch up by supporting and streamlining care design. To innovate, health system technology infrastructure must adapt to new models of care, not enforce rigidly encoded structures. Leaders across the hierarchy must doggedly champion a vision and purpose. Health systems must set eligibility criteria that empower staff to equitably reach more patients who, like Marilyn (the first patient), would describe acute care as "warm," "comfortable," and "wonderful."

DIHI remains committed to our mission to catalyze transformative innovations in healthcare. This project has been one of our most transformative to date (inventing things for markets that don't yet exist[6]). Our next step is to further support the case for economic viability. We look forward to supporting hospital at home programs in North Carolina and across the United States.

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Norine Chan
Norine is a third-year Duke medical student and 2021-2022 DIHI scholar working on the project "Identifying Inequities in Access to Organ Transplantation." Originally from Brooklyn, New York, Norine completed her undergraduate work at the City University of New York – Hunter College as a Macaulay Honors scholar and studied psychology, behavioral neuroscience, chemistry, and creative writing. Following graduation, Norine spent a year in Kaohsiung, Taiwan as a Fulbright teaching scholar before returning to New York City to obtain clinical experience as a medical assistant and ED medical scribe. Norine plans to pursue a career in general surgery and is deciding on further specialization among transplant, trauma, or surgical oncology. She also hopes to complete future research and education in public policy and healthcare delivery. In her free time, Norine loves live music, grabbing dinner and drinks in new cities, and critically analyzing everything from contemporary literature to her latest streaming obsession. You can find Norine enjoying a flat white or chai latte at her favorite Durham coffee shop, Cloche Coffee.



Kim Niederhoffer
Kira is a third-year medical student at Duke and a 2021-22 DIHI scholar. Her primary project this year will be "Predicting Hospital Admissions and Emergency Room Visits from Immune Related Adverse Events." Before coming to Duke, Kira graduated from the College of the Holy Cross and spent three years in a translational oncology research lab in Boston. She hopes to pursue a career in internal medicine. In her free time, Kira enjoys orchestrating book clubs, going on hikes, and trying new board games. You can currently find her working on her Wingspan strategy.



Tim Ochoa
Tim is a third-year medical student at Duke and a current DIHI scholar primarily working on the "Building a Predictive Model for Survival after Lung Transplantation" project. Before moving to Durham, Tim spent his gap year at the New York State Psychiatric Institute at Columbia University exploring predictive models for sudden infant death syndrome (SIDS), autism, and fetal alcohol syndrome in the early fetal and neonatal periods. Since then, he has become passionate about the intersection between machine learning and healthcare. Tim is also interested in global health, health equity, and mental health. In his free time, he loves playing soccer, exploring the beautiful nature of North Carolina, and watching exciting superhero films/shows. Thanks to long hospital days, Tim is becoming an avid coffee drinker—with plenty of milk and sugar of course, coffee is bitter!



Hayley Premo
Hayley is a third-year medical student at Duke and a 2021-22 DIHI scholar. Her primary project is "A Geriatric-Specific Morbidity and Mortality Risk Stratification Tool (GEMMSTOR) for Older Surgical Adults." As an aspiring urologist, Hayley is interested in improving outcomes and addressing disparities amongst surgical patients. Although originally from Winston-Salem (a.k.a., the birthplace of Krispy Kreme), Hayley completed her undergraduate education at Christopher Newport University, where she studied Neuroscience and Leadership. In her free time, she enjoys making pottery, building miniatures, and spending time with her dogs around downtown Durham.



Rebecca Shen
Rebecca is a third-year Duke medical student and a DIHI scholar working on the 2021-2022 RFA project "Improving Equity and Value of PAD Care at a Population Level." Currently undecided on specialty, she is considering primary care or pain medicine. She is also interested in using machine learning and technological innovation to streamline provider workflows and improve how health systems serve broader patient populations. She enjoys a good mango green tea, even though the caffeine will probably keep her up all night.

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