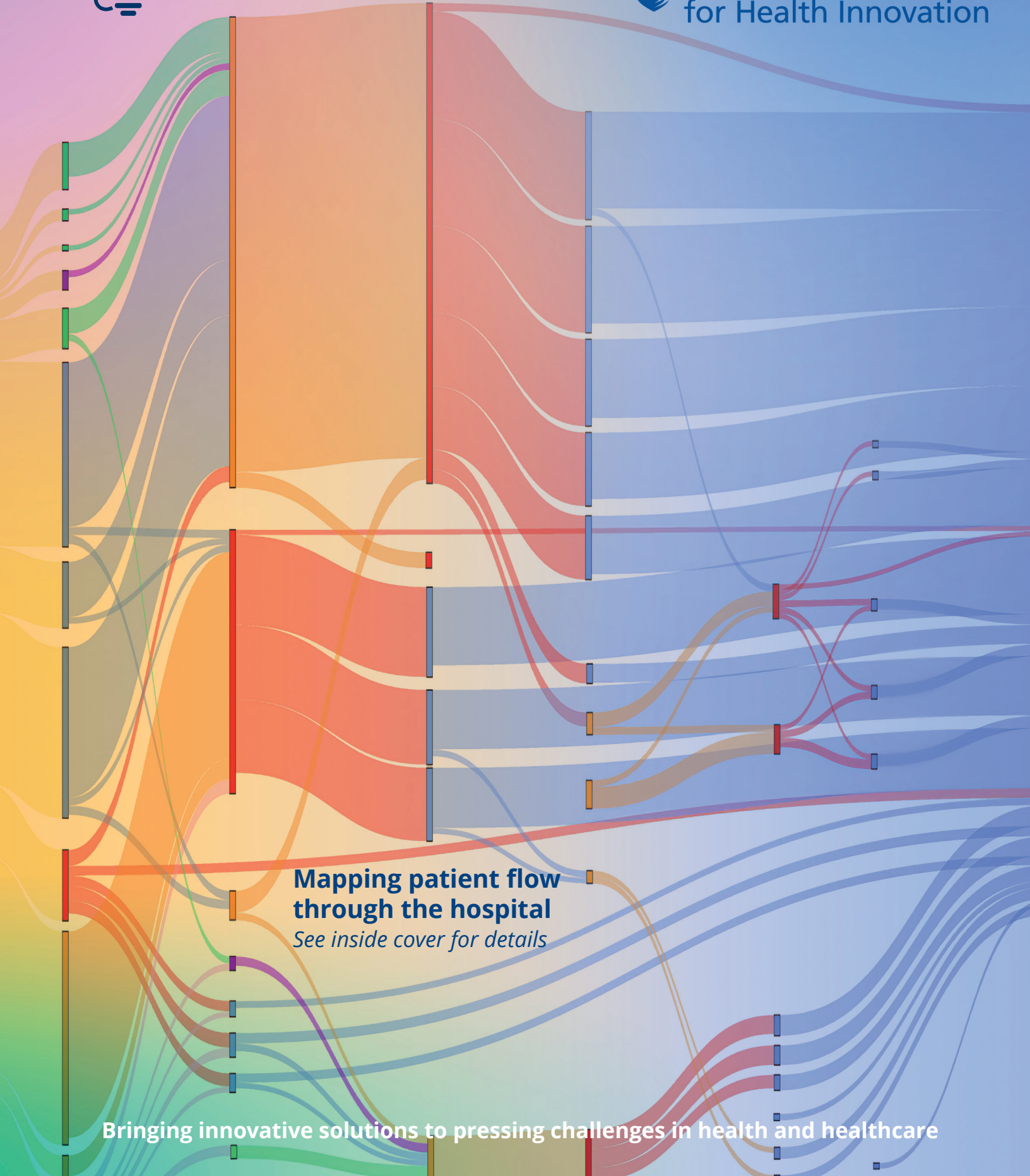




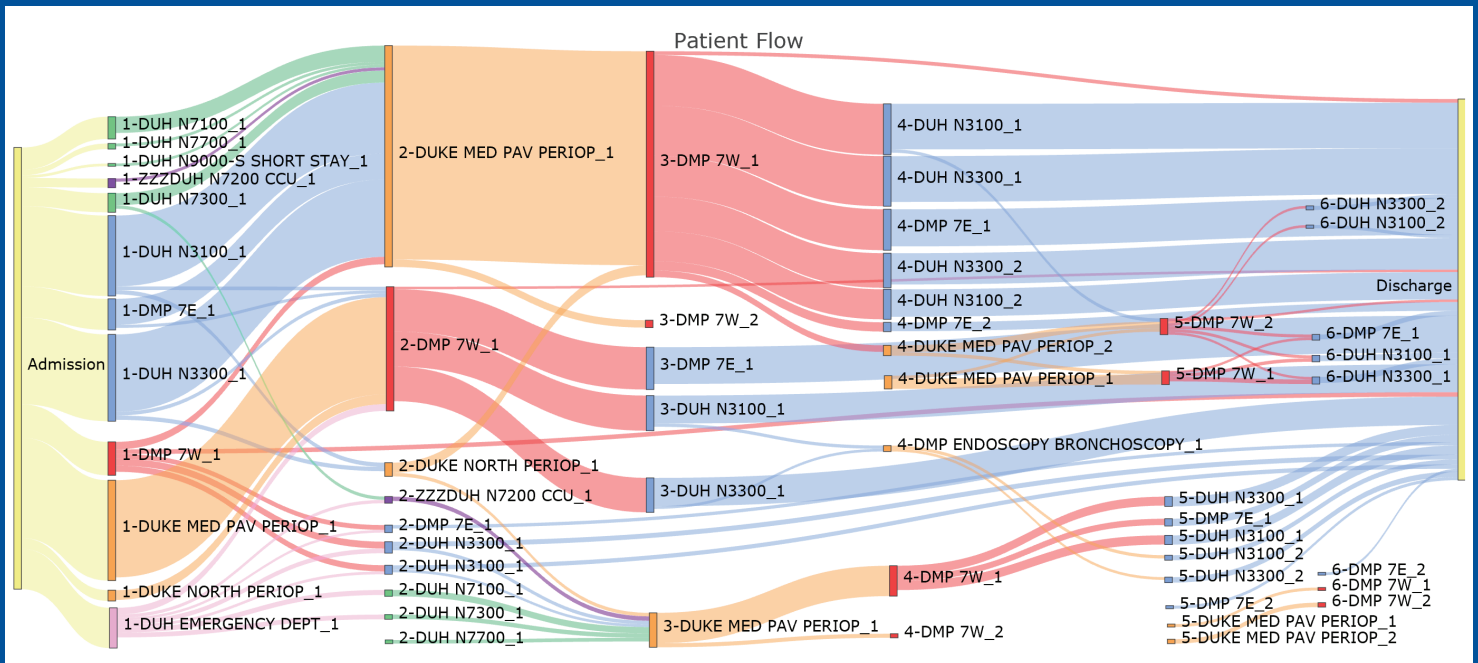
2019 Impact Report

 **Duke** Institute
for Health Innovation



**Mapping patient flow
through the hospital**
See inside cover for details

Bringing innovative solutions to pressing challenges in health and healthcare



ON THE COVER: Sankey diagram of patient flow through the hospital

Cohort: any patient encounters transferred to the Cardiothoracic ICU at some point during the hospital stay, 10/2014 – 08/2018. Length of stay > 30 minutes, >50 transfers across cohort for two given departments

Color representation:

- Red: CTICU
- Blue: step down
- Orange: surgery
- Pink: emergency
- Green: intermediate
- Purple: other ICU

Diagram created by Shujin Zhong

2019 Impact Report

Duke Institute for Health Innovation

5	LETTER FROM THE DIRECTORS
6	2019 DIHI RFA PROJECT SUMMARIES
6	PREDICTING HYPERGLYCEMIA Identifying Patients at Risk of Steroid-Induced Hyperglycemia
8	CARDIOGENIC SHOCK Early Identification of Cardiac Decompensation and Cardiogenic Shock
10	EVIDENCE-BASED LAB ORDERS High Value Analyte Ordering across the Duke Health Population
12	VIDEO VISITS
14	REDUCING RACIAL DISPARITIES
16	IDENTIFYING LVAD COMPLICATIONS Patient-Directed Acoustic Surveillance for LVAD Complications
24	REDUCING IN-HOSPITAL MORTALITY
26	PROJECT NORMAL ECHO Utilization of Machine Learning to Read Transthoracic Echocardiograms
30	ePRO IN CANCER CARE Optimizing Patient-Reported Outcomes Data and Workflows in Maestrocare
34	CODE BLUE MOBILE APP
35	VOICES OF DUKE HEALTH
39	RFID TRACKING Surgical Instrument Tracking and Optimization of the Operating Room
42	DIHI TEAM

DIHI PERSPECTIVES

15	Machine Learning
20	Evaluating Health Innovations
23	Innovation Implementation
29	Data Pipeline
32	Innovation Jam

DIHI INNOVATION SCHOLARS PERSPECTIVES

7	Morgan Simons
13	Christelle Tan
25	Nathan Brajer
31	Heather Rosett
38	Karishma Sriram
41	Josh Helmkamp

From the Directors

2019 HIGHLIGHTS FOR DUKE INNOVATORS AND SCHOLARS

As health care systems face increasing costs and reimbursement uncertainty, value-based models of care and population health management have gained significance. To reflect these realities, the portfolio for the Duke Institute for Health Innovation (DIHI) has continued to evolve to meet these challenges and address the needs of our patients. In this past year, we have focused our efforts in quality and patient safety, preventing hospital acquired infections, team-based care models, novel patient interactions and population health. These serve as the priorities for our two major innovation sourcing platforms: the DIHI RFA and the Duke Health Innovation Jam.

While supporting these priority areas, three trends have emerged:

- a need for a substantial expansion in our capabilities to implement machine learning and data science projects
- a greater focus on cross-campus collaboration and partnership with like-minded entities internal and external to Duke
- a renewed emphasis on training the next generation of innovators and data scientists.

Perhaps the most significant byproduct emerging from our innovation portfolio is the DIHI Data Pipeline—a foundational, fully-automated data curation tool enabling data liquidity which accelerates quality improvement, learning health, research and innovation projects. By integrating and standardizing the EHR, clinical outcomes, claims and other data sources the pipeline provides comprehensive, timely, accurate and linkable information to support system-wide innovation and transformation. Successful implementation of the data pipeline across the health system will allow us to have significant impact on care across clinical areas and could help us to more accurately predict and hence prevent adverse outcomes.

The past year has provided opportunities to grow existing partnerships with the Population Health Management Office, Clinical and Translational Science Institute, Forge, Schools of Engineering and Nursing, among others, while establishing new ones such as AI.Health. In partnership with Duke Health Technology Solution (DHTS), we are creating core infrastructure for deploying AI and machine learning solutions for health care. We look forward to continuing to engage with these multidisciplinary teams and bring new innovations to bear with the ultimate goal of improving patient outcomes, reducing cost and delivering the highest quality care.

One of our proudest achievements over the past two years is our broad engagement with trainees, faculty and staff across Duke Health. We are very pleased to have provided an immersive innovation experience for medical school students and residents while supporting faculty and staff in their innovation and entrepreneurship endeavors.

For the current academic year, four new areas have emerged as strategic priorities: new models for care delivery; enhancing provider and staff well-being and experience; enhancing patient engagement and experience; and accelerating population health solutions and strategies. We look forward to sharing the progress and achievements in these areas in our next update.

Sincerely,

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

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

“IN THIS PAST YEAR, WE HAVE FOCUSED OUR EFFORTS IN QUALITY AND PATIENT SAFETY, PREVENTING HOSPITAL ACQUIRED INFECTIONS, TEAM-BASED CARE MODELS, NOVEL PATIENT INTERACTIONS AND POPULATION HEALTH.”



THE PREDICTIVE MODEL GATHERS RISK FACTOR DATA FROM ADULT PATIENTS RECEIVING HIGH-DOSE CORTICOSTEROIDS TO IDENTIFY THOSE AT RISK OF DEVELOPING STEROID-INDUCED HYPERGLYCEMIA.

Predicting Hyperglycemia

IDENTIFYING PATIENTS AT RISK OF STEROID-INDUCED HYPERGLYCEMIA

The purpose of this project is to develop a predictive model to identify patients at risk of steroid-induced hyperglycemia and optimize treatment approaches for these patients. The predictive model gathers risk factor data from adult patients receiving high-dose corticosteroids to identify those at risk of developing steroid-induced hyperglycemia. Once the model identifies patients, a clinical team will review the patients and determine if interventions in care are warranted. Once the model and workflow are tested, the next phase of the project is to enhance the model so that treatment approaches for patients at risk of developing steroid-induced hyperglycemia can be determined.

Systemic glucocorticosteroids are prescribed for a variety of indications and may be used at high doses and for long durations in some patient populations. Unfortunately, exogenous steroids are frequently associated with a host of side effects including hyperglycemia, increased risk for infection, Cushingoid symptoms, increased risk of cardiovascular events,

TEAM

Ann McGee, PharmD, Tracy Setji, MD, Morgan Simons, Krista Whalen, Marshall Nichols, MS, Mark Sendak, MD, Finale Doshi-Velez, PhD, Joe Futoma, PhD

hyperlipidemia, development of diabetes, and others. Steroid induced hyperglycemia may occur in patients both with and without a history of diabetes. Due to the frequency of steroid-induced hyperglycemia and its association with poor outcomes, a tool that can standardize the approach of identifying and managing steroid-induced hyperglycemia is desired.

SOLUTION

Development of a machine learning model and complementary workflow was achieved by the team.

MODEL: identify patients at risk for developing steroid-induced hyperglycemia

WORKFLOW: make the outputs of the model actionable by clinician review



Various machine learning approaches were utilized to determine if a model could predict which patients receiving high dose corticosteroids would develop sustained hyperglycemia. A cohort of 11,995 inpatients seen at Duke University Hospital (DUH) between Oct 2014 and Aug 2018 was selected. Patients in this cohort were ≥ 18 years old and received high dose corticosteroids (≥ 20 mg/day of prednisone equivalents). Thirty-two features were chosen based upon the expertise of an interdisciplinary team including an inpatient endocrinologist and pharmacist. The outcome of hyperglycemic events was defined as patients having two blood glucose values above 180 mg/dL within 12 hours of corticosteroid administration. The models were evaluated using k-fold cross validation on data from DUH and validated on patient data sets from Duke Regional Hospital (DRH) and Duke Raleigh Hospital (DRAH). Model performance was evaluated using AUROCs and AUPRCs. Interpretation by two independent cardiologists.

A clinical workflow was created in coordination with a multidisciplinary team that included endocrinologists and pharmacists. Twenty hours were spent in creation and validation of this workflow. The purpose of the workflow was to facilitate integration of the machine learning model in the inpatient environment. The pilot of the workflow and model integration is being deployed in a single unit of Duke University Hospital where many patients receive a high dose of corticosteroids.

OUTCOMES

The predictive approach of the model can impact the safe care of patients. Each morning, the model generates a report of patients at risk of developing steroid-induced hyperglycemia. Based on this report, the project team is in the process of validating the predictive model output via a pilot in the inpatient adult bone marrow transplant unit. A team that includes endocrinology fellows reviews the report and examines patient charts to determine whether intervention in the care of patients is needed to address the risk of hyperglycemia. Poster presentations were given at ADA and MLHC 2019 conferences. Once validation of the model and workflow is complete, next steps for integrating this model into clinical care will be assessed. 💡



“Working with DIHI has changed how I envision my future career; rather than focusing on purely clinical work, I now want to continue to apply the data science and implementation lessons I have learned to problems I encounter in my future clinical practice.”

Morgan Simons

During my year with DIHI, I have worked on several projects, but primarily focused on a project tackling the identification and treatment of patients with corticosteroid induced hyperglycemia. The goal of this project was to bring these patients to the attention of endocrinologists earlier in an effort to prevent the negative sequela of prolonged hyperglycemia. At the outset of the project, my role was to assist with data curation and analysis, but as project unfolded, I was offered the opportunity to take a larger role in the development of a machine learning model that identified which patients were at risk, and I took it. The awesome members of my team were willing to give me the space and opportunity to further my learning and delve into an area of research I had not worked in before. Because of their trust and support, I was able to build the model with the help of others, and it will soon be deployed with an accompanying clinical workflow in a pilot on the Bone Marrow Transplant Unit at DUH. Through this project I learned not only the hard skills of data science, but several soft skills around leadership strategies and team communication that I will use in my future career as an internist. Working with DIHI has changed how I envision my future career; rather than focusing on purely clinical work, I now want to continue to apply the data science and implementation lessons I have learned to problems I encounter in my future clinical practice.

¹ Cines DB, Blanchette VS. Immune thrombocytopenic purpura. *N Engl J Med*. 2002; 346: 995-1008.

² McKay LI, Cidlowski JA. Corticosteroids in the treatment of neoplasms. In: Kufe DW, Pollock RE, Weichselbaum RR, et al., ed. *Holland-Frei Cancer Medicine*. 6th ed. Hamilton, Ontario: BC Decker; 2003. Available from: <https://www.ncbi.nlm.nih.gov/books/NBK13383/>.

³ Sung AD, Chao NJ. Concise review: acute graft-versus-host disease: immunobiology, prevention, and treatment. *Stem Cells Transl Med*. 2013; 2: 25-32. .

⁴ Weiser MA, Cabanillas ME, Konopleva M, et al. Relation between the duration of remission and hyperglycemia during induction chemotherapy for acute lymphocytic leukemia with a hyperfractionated cyclophosphamide, vincristine, doxorubicin, and dexamethasone/methotrexate-cytarabine regimen. *Cancer*. 2004; 100: 1179-85.



CARDIOGENIC SHOCK IS A STATE OF CARDIAC DYSFUNCTION WHICH LEADS TO HYPOPERFUSION OF CRITICAL ORGANS AND CAN ULTIMATELY SPIRAL INTO A FATAL EVENT.

Cardiogenic Shock

EARLY IDENTIFICATION OF CARDIAC DECOMPENSATION AND CARDIOGENIC SHOCK

Cardiogenic shock is a state of cardiac dysfunction which leads to hypoperfusion of critical organs and can ultimately spiral into a fatal event. For the eight hundred patients who develop cardiogenic shock at Duke University Hospital (DUH) each year, their cohort's in-hospital mortality rate of 30% represents a challenging set of patients who often require care coordination across multiple cardiac subspecialty teams.

PROJECT GOALS

1. Develop a machine learning model to predict cardiac decompensation (v1: mortality)
2. Use Duke EHR data (Epic + Lumedx) to generate and validate a digital cardiogenic shock phenotype
3. Launch multi-disciplinary shock team
4. Implementation goals: create visual dashboard of Aims 1 and 2 & validate both the model and phenotype

TEAM

Ajar Kochar, MD, Will Ratliff, MBA, Sehj Kashyap, Aman Kansal, MD, Mark Sendak, MD, Michael Gao, Chet Patel, MD, Schuyler Jones, MD, Manesh Patel, MD, Zach Wegermann, MD, Kelly Kester, DNP, Cory Miller, RN

SOLUTION AND OUTCOMES

The Heart Center at Duke identified the opportunity to assess whether a new, expedited, team-based treatment intervention on these patients could improve the process of care and impact clinical outcomes. To support this new treatment intervention, Duke Cardiology and the Duke Institute for Health Innovation (DIHI) formed a transdisciplinary team to identify the patients who develop clinical deterioration and cardiogenic shock in real-time by creating an automated electronic phenotype, and to develop a machine-learning model for predicting in-hospital mortality for all Duke cardiac patients using patient baseline and hospital stay data extracted from the EHR. We will then combine the digital phenotype and model output in a visual tool to catalyze



the deployment of the new team-based workflow and to help inform the clinical team's treatment decisions.

We surveyed 230 Duke Cardiology clinicians on the potential value of a rapid intervention team and of a real-time mortality model output on patient care, and found that 80% of both physician and nurse sub-groups estimated a high or medium amount of value added by those care strategies for cardiology patient's presenting early warning signs of deterioration. We designed a new multi-disciplinary cardiogenic shock team (Shock Team) workflow, which begins with the cardiac intensive care unit (CICU) fellow calling together the Shock Team after assessing a patient at risk for deterioration. The team consists of physicians in advanced heart failure, interventional cardiology, cardiac surgery, and the CICU. This team integrates the clinical tool (Shock Dashboard) that we developed into the care discussion to help risk stratify and determine the need for additional medical interventions, such as mechanical circulatory support.

Our team developed a four-part cardiogenic shock phenotype. The phenotype development cohort consisted of all adult DUH Cardiology patients over a 47-month timespan from October 2014 to August 2018, totaling 12,613 unique patients and 18,614 unique encounters. Our team used 377 clinically determined predictors including patient labs, vitals, and interventions to fit a lasso-penalized logistic regression, a ridge regression, a random forest, and an extreme gradient boosted decision tree model to predict inpatient mortality within a 48-hour window for DUH Cardiology patients at the time of admission into cardiology service (t0), and also at 4 hours (t4), 8 hours (t8), and 16 hours (t16) into the cardiology service admission (all maintaining the 48-hour window for mortality prediction). Inpatient mortality occurred in 180 (4.1%) of encounters. Models were developed on a subgroup of 2,721 patients (80%) and 3,543 encounters and models were evaluated on a held out, randomly-selected set of 680 patients (20%) and their 893 total associated encounters. We used cross-validation within the training set to tune model hyperparameters.


Outcomes of the project

Resulting models for t0 had predictive performance area under receiver operator characteristic (AUROC) curve values ranging from 0.74 to 0.78 and area under precision recall (AUPR) curve values ranging from 0.06 to 0.09 calculated on the validation set. The t4, t8, and t16 models saw improved performance, ranging from 0.87 to 0.93 AUROC curve values, with AUPR curve values ranging from 0.20 to 0.36. Through additional analysis

observations and discussion with cardiology leadership, we hypothesize that our performance improvement from the t0 model to the subsequent t4, t8, and t16 models largely due to the data available as the patient encounter evolves. We found that, for about half of our cohort, the time of admission into cardiology service (t0) corresponded to the time of admission into the hospital. Given that many of our model inputs involved lab results and procedures, we saw

Among our cohort of encounters, 4,767 (25.6%) met the phenotype. Within the phenotype, there are four definitions with specified criteria. Definition 1 specified concurrent reduced blood pressure and hypoperfusion indicators, as well as fever exclusion indicators during the encounter, with initial results showing that 1,867 of 18,614 cohort encounters (10.0%) met the definition. Phenotype definition 2 specified new or increased vasopressor administrations, with 2,160 of 18,614 encounters (11.6%) meeting this definition. Phenotype definition 3 involved identifying patients with a mechanical support device, with 2,088 of 18,614 encounters (11.2%) meeting this definition. Phenotype definition 4 involved identifying patients with worsening cardiac hemodynamics, with 1,246 of 18,614 unique encounters (6.7%) meeting criteria. The Shock Team was launched in April 2019, with 8 calls thus far to activate the team in response to a cardiac patient who seems to be deteriorating. Of those calls, two resulted in expedited surgeries (one VAD and one aortic valve surgery), one resulted in stabilization for advanced heart failure therapies, and one resulted in treatment with medications and PCI.

Next steps

Duke Heart and DIHI are collaborating to implement the phenotype dashboard and model to support real-time identification of patients experiencing or at high risk of experiencing cardiac decompensation. The model outcome will expand to include components of the phenotype itself, which includes additional criteria on respiratory decline and respiratory intervention. The mortality modeling work from this project will also be carried forward to inform a model to predict mortality within 48 hours for all patients. 



IN THE ERA OF VALUE-BASED CARE AND CONSTRAINED RESOURCES, THERE IS A NEED TO REDUCE PRACTICE VARIABILITY, OPTIMIZE LIMITED HEALTH CARE RESOURCES, AND DELIVER THE HIGHEST QUALITY CARE TO PATIENTS.

Evidence-based Lab Orders

HIGH VALUE ANALYTE ORDERING ACROSS THE DUKE HEALTH PATIENT POPULATION

Healthcare costs are increasing at an unsustainable rate; up to 30% (over \$750 billion annually) has been reported as wasted care that is potentially avoidable or unnecessary and would not negatively affect patient care if eliminated. In the era of value-based care and constrained resources, there is a need to reduce practice variability, optimize limited health care resources, and deliver the highest quality care to patients. The implementation of electronic health records (EHR) has created a vast repository of granular patient and population data. However, accessing the right information at the right time is complex and challenging, particularly in a time-compressed care delivery environment.

This project focuses on the design and implementation of EHR-based clinical decision support tools to facilitate a system-wide intervention for presenting real-time clinical information in the routine care workflow to optimize laboratory ordering decisions. A

TEAM | Laura Roe, Mike Datto, MD, Brian Griffith, MD, Susan Spratt, MD, Andrew Crichton, Tres Brown, Krista Whalen, Mark Sendak, MD, Heather Rosett, Michael Gao

key underpinning of this work includes standardizing laboratory analyte orderable and historical naming, in order to present relevant previous results at the point of order entry. The presentation of the relevant lab results saves provider and system time, and decreases both the number and frequency of unwarranted, unnecessary, or repeat laboratory tests.

PROJECT OBJECTIVES

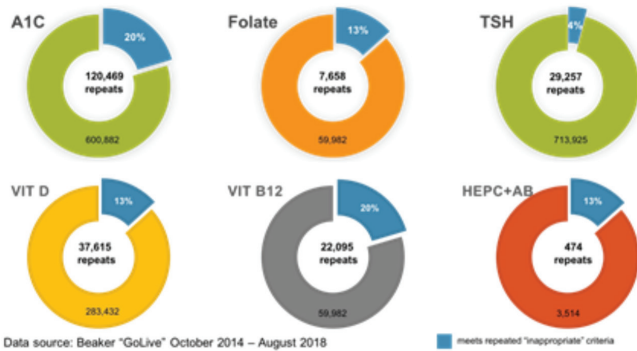
Locating historical relevant lab analyte results at point of care can be time consuming and incomplete due to the fragmentation of the health system; frequently leading to redundant and unnecessary testing. By employing a lab clustering algorithm to present relevant historical lab results at the point of care, clinicians have actionable information available for rapid and relevant clinical



decision making. Using existing EHR-based tools we selected 5 lab analytes to pilot in order to save provider and system time, reduce inappropriate or redundant lab testing, and improve the care of our patient population.

The initial phase of the pilot involved a retrospective analysis to identify “hot-spots” (clinics, departments, inpatient units) where specific lab analytes were frequently ordered inappropriately and to develop clinical partners to test pilot ordering interventions.

Analytes selected for the pilot phase: Hemaglobin A1C (Hgb A1C), Thyroid Stimulating Hormone (TSH), Vitamin D, Vitamin B12, and Folate. Hepatitis C Antibody was added in February 2019. The following represents the characterization of the opportunity across the identified analytes:



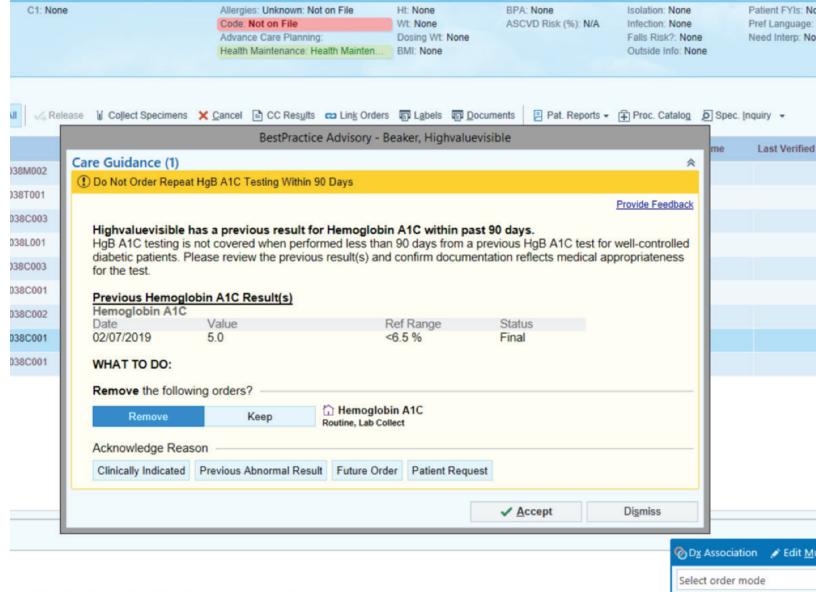
SOLUTION AND OUTCOMES

Leverage a technology solution to collect data from disparate sources, analyze the data against defined rules for clinical criteria for repeating laboratory testing and deliver actionable information to support clinical decision making. We evaluated several options existing outside and within Epic. We aimed to reduce workflow friction, find the best fit to minimize disruption, and tailor the information. We decided to use existing Epic functionality, Best Practice Advisory (BPA).

When evaluating the options for the pilot and clinical decision support (CDS) we used the framework of the five rights of clinical decision support: right information, right person, right channel, right CDS intervention format, and right point in the workflow.

Silent BPAs were implemented September 2017 and continue to run in Epic for systemwide data collection.

An abstract was submitted to High Value Care Practice Academic Alliance annual meeting.



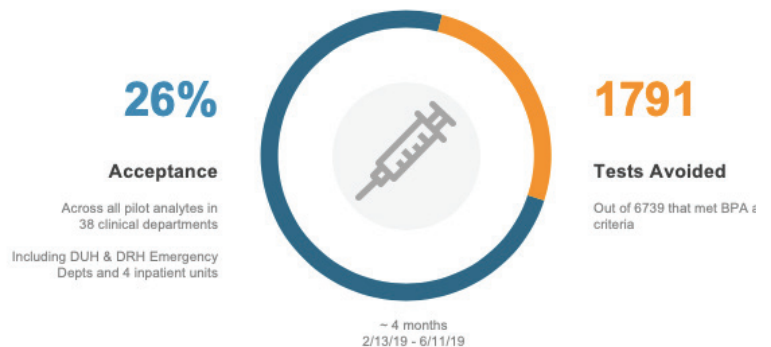
Next steps

We continue to monitor the impact of the initial phase of the BPA roll-out, particularly where we are effective in avoiding a repeat test and reasons for override.

The following represent our top priorities:

- By analyte characterize compliance and reasons for dismissal
- Evaluate the need to add or change current BPA rules
- Correlations between time of day, site of care, clinician role
- Translate our experience to generalizable knowledge, specifically around influencing decision making and delivering high value care
- Financial evaluation with PRMO on HgBA1C impact
- Qualitative interviews with clinicians
- Identify additional analytes with EDROC

Ordering Impact



Video Visits

IMPROVING PRIMARY CARE ACCESS FOR RESIDENTS AND FELLOWS

Residents are significantly less likely than demographically similar peers to have a primary care provider or dentist, or to have participated in routine health maintenance¹. GME trainees often have difficulty seeing primary care providers during routine business hours, largely due to rigorous residency schedules².

At Duke, there are several additional factors limiting primary care access. First, population growth in the Triangle area has increased overall demand for primary and urgent care visits making on demand access more challenging. Second, most primary care clinics and providers at Duke are not within walking distance of Duke University, Duke Regional, or Durham VA hospitals where most trainees practice, thus requiring trainees to drive to PCP appointments and be away from work.

OBJECTIVES

1. Increase support and awareness of concierge scheduling for GME trainees within Duke Primary Care to increase the number of trainees who are established with a DPC provider.
2. Perform an environmental assessment of relevant stakeholders to understand their needs and concerns regarding a video visit platform
3. Develop a video visit platform
4. Pilot video visits as a method to increase primary care access for trainees

SOLUTION AND OUTCOMES

We developed an innovative GME Trainee Primary Care Video Visit Program within Duke Primary Care for current and future GME trainees. The intervention allows GME trainees access to virtual primary care services for both acute and chronic care conditions. Thus, trainees are able to access primary care services without having to leave the hospital. Furthermore, support of the concierge line allows trainees to access and establish primary care with greater flexibility by increasing the number of appointment slots available to trainees.

We have held seven resident feedback and focus group sessions, built and tested the video visit platform, and presented the service at four GME orientations. Two providers were identified to conduct video visit appointments. Video visits were available to trainees starting July 2018. Since then, 18 video visits have been

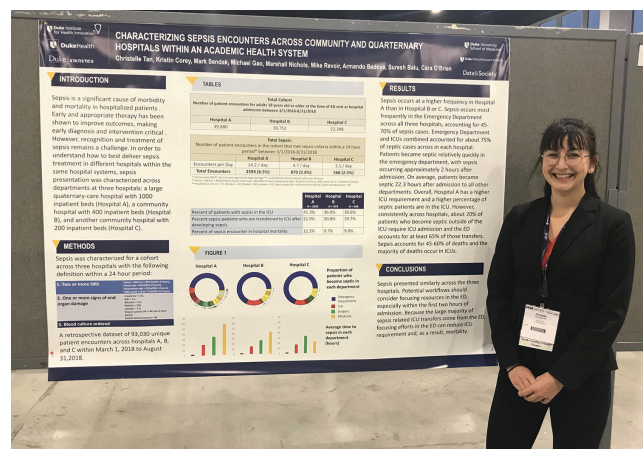
TEAM

Kevin Shah, MD, MBA, Dr. Catherine Kuhn, MD, David Turner, MD, Elizabeth Long, MA, Heather Marsteller, MBA, Alexander Borun, MD, John Anderson, MD, MPH, Krista Whalen, Christelle Tan

completed. Out of video visits that were completed in 2018, 100% of patients were satisfied with the telehealth experience, connected easily to the platform, and felt the visit was just as effective as a face to face visit. While the video platform functioned as planned, the demand for video visits was not as high as expected.

On the other hand, we have seen a much larger utilization of the concierge line than the video visits. 147 calls were answered and handled from October 2018 to April 2018. Through a review of recorded concierge line calls, we can see that the concierge line is an effective way to connect trainees to primary care. Out of the 142 available recordings, 111 (78.2%) appointments were scheduled, and the leading reason for an appointment not being scheduled was because the caller requested an appointment with a provider who was not in the Duke Primary Care practice group (N=12). The recordings also revealed low overall demand for video visits. 126 callers (88.7%) requested in-person appointments while only 16 (10.9%) requested a video appointment.

Despite low utilization of the video visits, survey results demonstrate decreased barriers to primary care after implementation of this service. When we compare the results of the annual GME wellness survey before and after implementation of our interventions, we see a significant decrease in barriers to accessing primary care services, from 58.10% to 30.85% ($p < 0.0001$), and a significant decrease in delays in access to primary care, from 27.00% to 20.92% ($p=0.023$). Out of residents who did experience delays, there was a statistically significant reduction in scheduling barriers (81.59%, 70.36%, $p=0.04$) and untimely appointments (59.19%, 40.68%, $p=0.0039$).



The availability of resources to connect patients to primary care greatly reduces trainee perception of barriers to health care and provides trainees a convenient mechanism to schedule flexible primary care appointments. Well-being and burnout is multifactorial and it is possible that a reduction in perceived barriers to health care will improve overall trainee wellbeing and hopefully contribute to decreasing burnout.



“This year was eye opening in a lot of ways, but particularly I learned a lot about how large health systems prioritize and evaluate health care improvement projects.”

What's next?

The analysis demonstrates that the concierge line is effective both in improving trainee perceptions around access and barriers to care, as well as improving trainees' ability to schedule with primary care providers. The analysis did show that residents frequently request more flexible locations and hours. Duke Primary Care does not have locations at the hospital, and trainees often ask for primary care locations near the hospital. In addition, trainees are often requesting evening or weekend appointments—while some DPC clinics have this availability, this is an opportunity that could be expanded.

In addition to primary care, there were notable requests for similar access to specialty care. Expanding the concierge line to schedule appointments outside of Duke Primary Care to include obstetrics, gynecology, and pediatrics, would address an unmet need among trainees where there is clearly demand.

Finally, low demand for video visits suggests there could be an alternative service that is more useful for trainees. Many callers to the concierge line were scheduling appointments for specific requests such as medication refills, lab orders, or imaging orders. An asynchronous service where trainees are able to communicate with physicians via a more responsive system than Epic MyChart, could be helpful in those cases. This service would allow trainees to fulfill specific medical requests at a convenient time and location and with a 24 hour expected turn-around time (72 hours is the institutional expected turn-around time for Epic MyChart). 💡

¹ Cedfeldt, A. S., Bower, E. A., Grady-Weliky, T. A., Flores, C., Girard, D. E., & Choi, D. (2012). A comparison between physicians and demographically similar peers in accessing personal health care. *Academic Medicine: Journal of the Association of American Medical Colleges*, 87(3), 327–331. <https://doi.org/10.1097/ACM.0b013e3182448731>.

² Eckelburry-Hunt J, et al. Changing the Conversation From Burnout to Wellness: Physician Well-being in Residency Training Programs. *J Grad Med Educ*. 2009 Dec; 1(2): 225–230.

Christelle Tan

During my DIHI year I worked primarily on two projects: 1. a video visit project to increase access to primary care among GME trainees, and 2. an evaluation of a pilot to improve sepsis bundle compliance at Duke University Hospital. For the video visit project, my initial goal was to evaluate video visit functionality—does the platform work, are trainees satisfied with the service, do the video visits result in prescriptions, referrals, labs, or close follow up? However, only a small amount of video visits were requested by GME trainees so the analysis became an interesting investigation into why video visits were not being scheduled and what would be a more useful resource for GME trainees. For the sepsis analysis, I was able to develop data science skills to do an analysis of how and where sepsis develops across Duke's three hospitals, evaluate sepsis bundle compliance across all three hospitals, and evaluate mortality and ICU requirement at DUH before and after the pilot.

This year was eye opening in a lot of ways, but particularly I learned a lot about how large health systems prioritize and evaluate health care improvement projects. Being able to take part in the DIHI RFA application review process and hear from healthcare leaders about the changes they would like to see revealed a new yet crucial aspect to healthcare innovation. This year, I was also able to participate in the Learning Health Systems Training Program, a program where primarily residents and fellows are able to attend seminars held by Duke leadership to help develop and evaluate their own independent projects. Participating in this program in addition to working with DIHI, demonstrated the breadth of projects occurring at Duke and how important it is for physicians to have the capacity to work on improvement the quality of patient care.

I am planning on applying to be a pediatric resident this fall. In the long term, I would like to work as a general pediatrician within an academic medical center. I hope to be able to split by time between clinic and program development work. I am most interested in the ways clinics can be better equipped to address patient psycho-social needs and would like to spend a significant part of my career building the infrastructure and connections to do so within my future clinic. The crux of this dream is working in a clinic that values innovation. This means that clinic leaders are interested in solving problems in novel ways, that they are open to piloting projects, and that they are willing to encourage innovation among their staff by providing compensation and dedicated time to create and evaluate improvement projects. I am very excited about the amount of innovation I observed during my year at DIHI, and I hope I continue to be inspired by the work of my colleagues wherever I work in the future.

Reducing Racial Disparities

IN UNMET PALLIATIVE CARE NEEDS AMONG INTENSIVE CARE UNIT FAMILY MEMBERS WITH A NEEDS-TARGETED APP INTERVENTION

As a part of a larger multi-year clinical trial, the team developed a mobile application (ICUconnect) to address the barriers patients, families, and providers experience in addressing and identifying unmet palliative care needs among diverse patients and family members.

There is a medical literature spanning decades that documents poor quality palliative care delivery as well as poor communication between ICU clinicians and families/patients. These deficits are worse when non-White families/patients are involved. The team is interested in addressing these issues, with particular attention to ICU-based health disparities in palliative care quality.

SOLUTION AND OUTCOMES

Our solution was to develop an app that actually allows assessment of the gold standard for palliative care: unmet needs. The ICUconnect app allows families to self-report unmet palliative care needs across all 8 domains of palliative care quality over time. These data are then shown in a simple web-based visualization for ICU

TEAM

Christopher Cox, MD
Sharron Docherty, PhD
Isaretta Riley, MD

clinicians, along with tips on how to address each.

We built a web app, performed successful usability testing, and have now implemented it in an ongoing clinical trial that has an expected enrollment period of 3 years. Enrollment is currently ongoing.

An intervention disclosure form was filed with Duke Office of Licensing & Ventures (OLV). Also, we have been awarded another NIH R01 grant for work that extends this concept by integration with the electronic health record.

This work has been presented at multiple Duke conferences, including grand rounds.

NEXT STEPS

First we need to complete the clinical trial! However, we are considering an NIH STTR application to explore commercialization of the product. 💡





“The ecosystem at Duke Health and Duke University is coalescing around the opportunity to lead the nation in developing and integrating ML/AI into clinical care.”

Mark Sendak, MD, MPP

Machine Learning and Augmented Intelligence Cross the Chasm in Health Care

Machine Learning (ML) and Augmented Intelligence (AI) crossed the chasm at Duke Health in 2019. The technologies and clinical integrations are now mainstream with great expectations to improve care delivery and outcomes. First was the launch of Sepsis Watch on November 5, 2018, after the DIHI team spent two and a half years developing and validating a deep learning model and building infrastructure to support real-time model integrations. This milestone marked the first time a deep learning technology was integrated into routine clinical care in the United States. The six-month pilot brought Duke University Hospital to the top decile in performance for the Centers for Medicare and Medicaid Services sepsis measure. Amidst the pilot success, five ML/AI projects were selected for funding through the DIHI RFA, including projects led by multiple clinical stakeholders involved in the Sepsis Watch program. In June 2019, the team at DIHI, in partnership with the emergency departments at Duke Regional Hospital and Duke Raleigh Hospital, implemented Sepsis Watch. In parallel, DIHI integrated two new ML/AI models for predicting steroid-induced hyperglycemia and inpatient mortality into clinical care.

The ecosystem at Duke Health and Duke University is coalescing around the opportunity to lead the nation in developing and integrating ML/AI into clinical care. Ai.health, announced in June 2019, will harness talent, energy, and resources to scale high impact collaborations to improve health care. Central to these efforts will be DIHI infrastructure, including a data pipeline, metadata curation engine, and model deployment platform that together enable rapid development, evaluation, and integration of ML/AI into clinical care. The work of health care data janitors and data engineers will now be supported with essential tools and utilities. Beyond technology, DIHI has been leading the development of best practices to ensure effective and rigorous development of health care ML/AI. Examples include the refinement of data quality assurance processes to ensure health care data are fit for use for ML/AI, transparent “Model Facts” labels to accompany ML/AI technologies, and standard processes for temporal and external validation ML/AI integrated into clinical care. DIHI contributed to the forthcoming guidelines set forth by the Machine Learning in Health Care (MLHC) community and will be hosting the MLHC conference in August 2020.

Central to DIHI’s mission is training the work force to guide healthcare into the 21st century. For the first time, DIHI led training programs concurrently for undergraduate students, graduate students, and medical trainees. Undergraduate students participated in a course taught by DIHI and the Social Science Research Institute to learn methods for evaluating health care innovations. Masters students participated in a course taught by DIHI and Duke Biomedical Engineering to learn about health care data science and gained hands on experience building ML/AI models on electronic health record data. Medical students participated in the DIHI Clinical Research & Innovation Scholarship to work on interdisciplinary teams building next generation technologies. For the first time, all five medical student scholars are co-authors on oral presentations that will be presented at MLHC 2019. 2018 to 2019 was a year filled with building and integrating products, building capabilities and capacity, and breaking down barriers to transform health and healthcare. We’re thrilled to see what we can do in 2020 and look forward to seeing you in Durham for MLHC 2020.



WE PROPOSED USING A NOVEL ACOUSTIC SURVEILLANCE STRATEGY TO ASSESS WHETHER COMPLICATIONS COULD BE PREDICTED USING ACOUSTIC CHARACTERISTICS OF LVAD DEVICES.

Identifying LVAD Complications

PATIENT-DIRECTED ACOUSTIC SURVEILLANCE FOR LVAD COMPLICATIONS

Left ventricular assist devices (LVAD) provide life-saving therapy for patients with advanced heart failure, but there is a high rate of complications with nearly 60% of patients readmitted to hospital within one year of therapy. Strategies to predict complications could potentially reduce hospitalizations and costs related to LVAD therapy. We proposed using a novel acoustic surveillance strategy to develop a predictor of impending LVAD complications using digital stethoscope recordings of ambulatory patients on LVAD therapy.

We recruited a cohort of 24 patients on LVAD support and trained them to record high quality digital stethoscope recordings of their LVAD sounds. Subjects recorded their own LVAD sounds and LVAD parameters weekly using stethoscopes and recorders provided to them by the study team. Subjects also completed a weekly online survey querying for adverse events and heart failure symptom burden (Kansas City Cardiomyopathy Questionnaire-12). Acoustic spectral analysis was used to analyze the digital stethoscope recordings to identify features associated with LVAD complications.

TEAM

Priyesh Patel, MD, Ravi Karra, MD, Boyla Mainsah, PhD, Leslie Collins, PhD, Cameron Olsen, MD, Will Ratliff, MBA, Xinlin Chen

PROBLEM

LVAD therapy is associated with a high rate of complications that are not predictable using standard clinical surveillance. Hence, we proposed using a novel acoustic surveillance strategy to assess whether complications could be predicted using acoustic characteristics of LVAD devices.

OUTCOMES

We have created the largest repository of acoustic data from an ambulatory cohort of LVAD patients and paired this with clinical and event data. 24 subjects were enrolled in the study, 18 with Heartmate 3 (HM3) and 6 with Medtronic HVAD. 16 events were identified among the 24 subjects at the time of this report (16/24 = 67%),

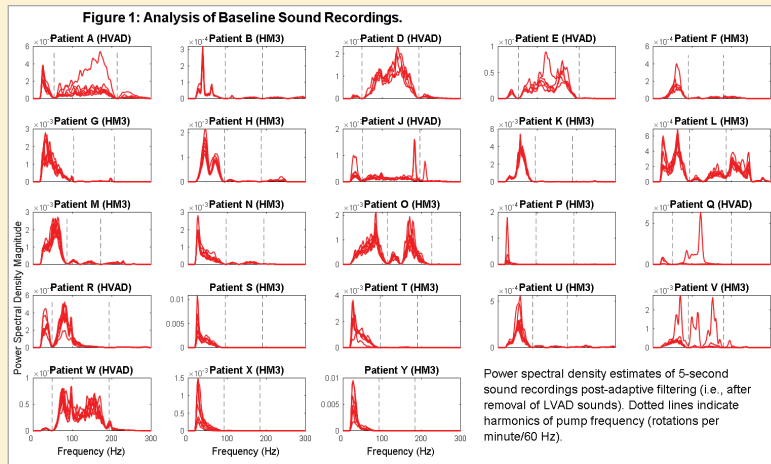
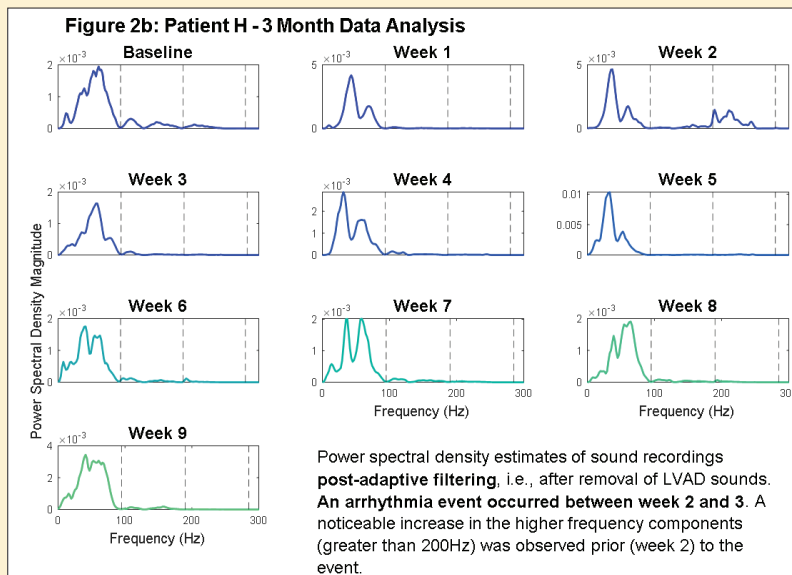
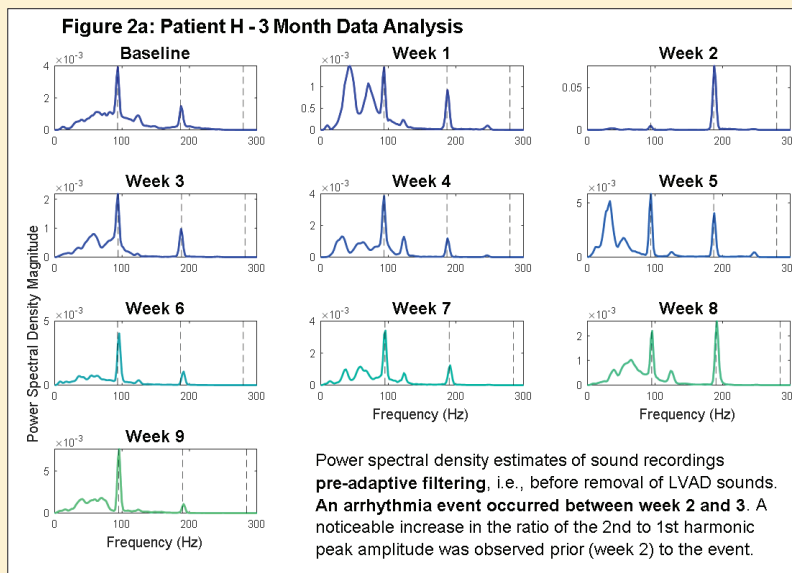


Figure 1: Power spectral density estimates of sound recordings post adaptive-filtering



Figures 2a and 2b: Patient H Data at 3 months



“WE HAVE CREATED THE LARGEST REPOSITORY OF LONGITUDINAL LVAD ACOUSTIC DATA REPORTED IN THE LITERATURE. WE WILL LEVERAGE THIS ROBUST DATASET TO CREATE PREDICTORS OF VARIOUS LVAD COMPLICATIONS”

Priyesh Patel, MD

with current total follow-up time ranging from 4-6 months among subjects.

Weekly participation rates for survey completion and acoustic recordings were consistently >80%. The study team collected LVAD acoustic recordings every 3 months at routine LVAD clinic appointments, which limits the ability to report on comprehensive results at the time of this report. For sound analysis, the signals were first downsampled and band pass filtered to restrict the frequency content of the signals to less than 500Hz, and adaptive filtering was used to isolate LVAD-specific frequency

components and better emphasize native heart sounds. The frequency content of the signals was analyzed pre- and post-adaptive filtering by estimating power spectral densities (PSDs) of five-second signal segments. In general, frequency peaks were observed in the first harmonic and multiples of the fourth harmonic of the pump frequency in the HVAD models, while peaks were observed at multiple harmonics of the pump frequency in the HM3 models; these findings are consistent with expectations based on the pump rotational frequency and number of blades. Baseline acoustic spectra for the 24 enrolled subjects after attenuating the LVAD-specific frequency components (i.e., post-adaptive filtering) are shown in Figure 1. Based on the PSD estimates, four clusters of heart sounds were identified, with one heart sound signature associated specifically with HM3 pumps. Additional signal analysis is ongoing to correlate spectral features with clinical outcomes.

SOLUTION AND IMPACTS


We have had the opportunity to analyze event data from one patient at the time of this report. Please see figures 2a and 2b. The patient was admitted with ventricular arrhythmia. In the week prior to the event, there was a noticeable increase in the ratio of the peak amplitude

of the second to first harmonic of the pump frequency. This was observed with and without adaptive filtering. The lead time from observation of change in acoustic ratio was 6 days. In particular, the cause of the subject’s ventricular tachycardia was thought to be related to septal/cannula interaction and possible hypovolemia. The LVAD speed was reduced to minimize change of interaction. The patient had another defibrillator discharge to treat ventricular tachycardia several months after this initial episode, though the acoustic data from this event has yet to be collected at the 6 month follow-up appointment.

We were able to observe changes in acoustic spectra in a patient with LVAD complication with adequate lead time for intervention to prevent complications. We similarly anticipate identifying changes from baseline acoustic spectra as we explore sound recordings from other patients who have had LVAD complications.

We have created the largest repository of longitudinal LVAD acoustic data reported in the literature. We and other groups have previously reported that LVAD thrombosis is associated with changes in acoustic spectra, and our work builds on this by showing that other LVAD complications can potentially be identified and perhaps predicted using an acoustic surveillance strategy. We will leverage this robust dataset to create predictors of various LVAD complications. In addition to drafting a manuscript with our baseline data, we are currently in the process of drafting several grants for ongoing research in this field, including foundation grants, NIH R03 to develop methodology, and an NIH R01 to build a larger validation cohort.

NEXT STEPS

We will continue to develop the idea and methodology of acoustic surveillance for LVAD complications. We envision that one day LVAD patients could simply use a digital stethoscope that would transmit data securely to a server that automatically analyses the acoustic spectra against a normal personalized template and alerts patients and providers of potential complications, much like current technology with implantable cardioverter defibrillators and pacemakers. 

Evaluating Health Innovations: **A partnership with Social Science Research Lab**

For the second year, DIHI has partnered with Social Science Research Lab (SSRL) to develop measurement and evaluation plans for DIHI funded projects. *Evaluating Health Innovations*, a semester-long course for undergraduates, was designed to provide students a broad view of the healthcare industry, health innovation, and social science research methodology and to provide students with the opportunity to partner with DIHI innovators to develop measurement and evaluation plans for innovation pilots. Throughout the course, students engaged in discussions with diverse healthcare professionals, from healthcare economists and nursing staff to medical students and data scientists. The full list of class sponsors and speakers is below. We are grateful for the time and enthusiasm class visitors devoted to this course.

Our goal is to engage students in discussions on a wide variety of health topics to spark interest in the healthcare field. *Evaluating Health Innovation* is a unique opportunity for students to gain experience participating in a health innovation project that is being implemented at Duke and to forge relationships with innovators across campus. This partnership is one of the ways in which we seek to educate and empower the next generation of healthcare leaders.

Class speakers:

George Cheely, MD, MBA
Phil Tseng, MD, MBA, MEd
Diana McNeil, MD
Rob Saunders, PhD
Dev Sangvai, MD, MBA
JP Sharp, JD, MPH
David Ridley, PhD
Blake Long, MD, MBA
Michael Gao
Kristin Corey
Theresa Coles, PhD
Alex Cho, MD, MBA
Donna Biederman, DrPH, MN, RN
Christelle Tan
Mark Sendak, MD, MPP

Class Sponsors:

Jessica Sperling, PhD
Jon O'Donnell, MD
Megan Gray, MSW
Krista Whalen



“Evaluating Health Innovations, a semester-long course for undergraduates, was designed to provide students a broad view of the healthcare industry, health innovation, and social science research methodology and to provide students with the opportunity to partner with DIHI innovators to develop measurement and evaluation plans for innovation pilots.”

Krista Whalen

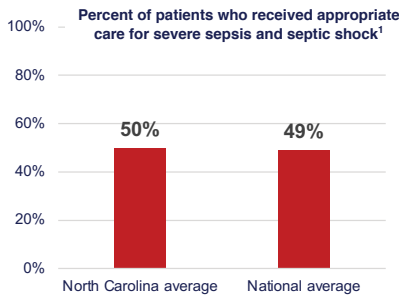




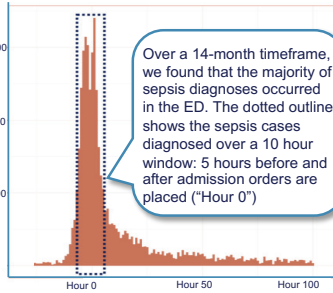
What is Sepsis Watch?

The Problem: Struggle with sepsis

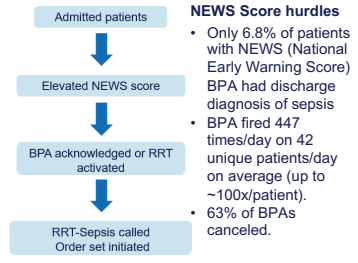
1 What is the problem? Sepsis



2 Where does the problem occur? The ED



3 Why are we failing to solve the problem today? Slow, false alarms



The Solution: Sepsis Watch

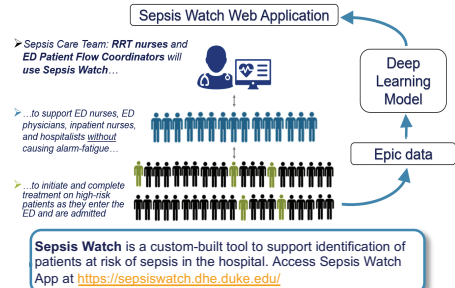
1 Define adult sepsis at Duke

2 or more SIRS criteria	<ul style="list-style-type: none"> Temperature >38°C or <36°C (6 hours) HR >90 (6 hours) RR >20 (6 hours) WBC count >12, <4, or % bandemia >10% (24 hours)
Suspect Infection	<ul style="list-style-type: none"> Blood culture order (24 hours)
1 element of end organ failure	<ul style="list-style-type: none"> Creatinine >2.0 (24 hours) INR >1.5 (24 hours) Total bilirubin >2.0 (24 hours) SBP <90 or decrease in SBP by >40 (6 hours) Platelets <100 (24 hours) Lactate ≥2 (24 hours)

2 Create machine learning model to predict sepsis quickly and accurately

- 42,000+ inpatient encounters analyzed at Duke Hospital over 14 months, 21.3% with a sepsis event.
- 32+ million data points incorporated: 25 million vital sign measurements, 2 million med admins, 5.2 million labs.
- 34 physiological variables (5 vitals, 29 labs).
 - At least one value for each vital in 99% of encounters.
 - Some labs rarely measured (2-4%), most measured 20-80% of the time.
- 35 baseline covariates (e.g. age, transfer status, comorbidities).
- 10 medication classes (antibiotics, opioids, heparins).

3 Design web application to show real-time model results and track treatment



DIHI

For more information, go to Just in Time Learning: <https://intranet.dh.duke.edu/hospitals/duh/duhedcouncil/SitePages/Current%20Roll%20Outs.aspx>

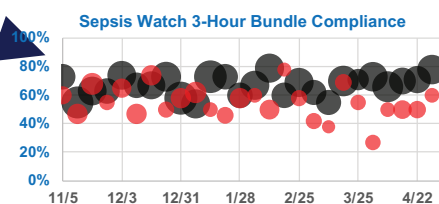
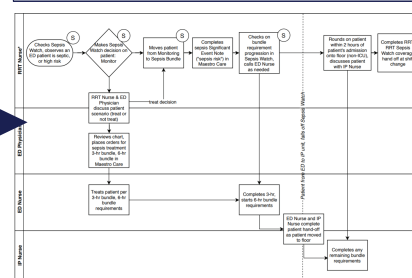
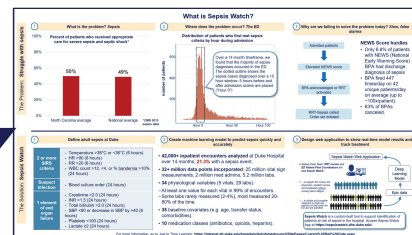
SB | 1

Anticipating and Overcoming "The Three Failures"

A pragmatic implementation of the Sepsis Watch solution

Failure	How to overcome	Tactics in practice
Failure to see	Communicate the vision	Train and educate: focus on critical need for change and the opportunity to run the experiment
Failure to move	Establish a clear path forward	With guidance of key stakeholders, establish workflow & roles
Failure to finish	Support frontline users for continued success	Create governance (include frontline users on committee!), report metrics to gain momentum

The Three Failures adapted from "Leading Strategic Change" – Black and Gregersen



Sepsis Watch Application Overview One-pager

A DIHI-designed single page overview of the solution, which was used for communication and training of the Rapid Response Team Nurses and other workflow team members



“It was humbling to observe the natural leadership roles taken on at each level of the Sepsis Watch project—the sheer energy and flexibility of the RRT nurses and ED staff, the support and proactivity of Duke Health Technology Solutions, and the operational effectiveness of Performance Services.”

Will Ratliff, MBA

Innovation Implementation

Soon after joining DIHI in July 2018, I had the unique opportunity to co-lead the pilot implementation of Sepsis Watch across Duke University Health System. As I enter my tenth year in the healthcare provider space, this experience has set Duke apart as a truly innovative health system with extraordinary staff who rise to the challenge to deliver collaborative, impactful patient care.

Sepsis Watch was the accumulation of a three year effort to bring machine learning into the hospital setting to predict a patient’s risk of becoming septic at some point in the next 36 hours. With guidance from Dr. Cara O’Brien and other clinical leaders at Duke, the DIHI project team developed a sepsis definition based on criteria captured in the electronic medical record in real-time. The team then incorporated that definition into a platform to predict and facilitate management of sepsis in the emergency department, which was identified as having the highest volume of sepsis events in the hospital. My role focused on integrating the Sepsis Watch solution into an effective yet minimally burdensome workflow for the front line staff involved and then on implementing that solution across the emergent care delivery settings within Duke Health.

In the months leading up to the pilot’s go live this past fall, the project team partnered with the Rapid Response Team (RRT) nurses from the Cardiac Intensive Care Unit and others to finalize the team members and mechanics for the new Sepsis Watch workflow. Beginning on November 5th, 2018, RRT nurses reviewed new patients as they entered the Duke University Hospital (DUH) Emergency Department who either met sepsis criteria or were at high risk of meeting sepsis criteria, as evaluated every five minutes by our model and displayed on the Sepsis Watch application. The RRT nurse then contacted the ED physician in charge of that patient’s care, as identified through the patient’s bed location on the app. Upon a positive diagnosis of sepsis by the ED physician, the RRT nurse would interact with the application to virtually “move” the patient into a bundle treatment pool on the Sepsis Watch application, which then converted to a semi-automated 3-hour and 6-hour SEP-1 bundle compliance tracking mechanism. As a final step, the RRT nurse utilized the app to help close gaps on bundle compliance as the patient transitioned from the ED to the floor.

A Governance Committee was established to steer the project through its six month pilot period. Sitting in on this committee, RRT nurses and ED physicians provided first-hand feedback on the workflow and led iteration of design improvement updates to further refine the Sepsis Watch application into an even more efficient and effective platform, which was updated based on feedback in February 2019. The DIHI team continued to learn from our clinical teammates within Duke University Hospital through the end of the pilot phase on May 5th, 2019. We then applied those learnings to lead successful implementations of the Sepsis Watch application and tailored workflows at Duke Raleigh Hospital (DRAH) and Duke Regional Hospital (DRH), as part of a Care Redesign partnership with Duke Health’s Performance Services. We are now continuing to evolve these site-specific solutions at DUH, DRAH, and DRH to facilitate seamless surveillance of new patients at risk of sepsis in their respective emergency departments.

It was humbling to observe the natural leadership roles taken on at each level of the Sepsis Watch project—the sheer energy and flexibility of the RRT nurses and ED staff, the support and proactivity of Duke Health Technology Solutions, and the operational effectiveness of Performance Services. We are excited to observe findings from the Center for Medicare and Medicaid Services which indicate a 2X improvement in 3-hour bundle compliance for Duke University Hospital during the Sepsis Watch pilot period when compared to the prior two year average compliance rate. We are currently evaluating the pilot phase to confirm Duke’s ascension into a national leader for treatment of sepsis in the acute setting.



EARLY IDENTIFICATION OF PATIENTS AT HIGH RISK OF IN-HOSPITAL MORTALITY MAY IMPROVE CLINICAL AND OPERATIONAL DECISION-MAKING AND IMPROVE OUTCOMES FOR THESE PATIENTS.

Reducing In-Hospital Mortality

Reducing in-hospital mortality is a key quality and safety priority across hospitals in the United States. Unfortunately, an average of 2% of patients admitted to US hospitals die during the inpatient admission. For some patients, particularly those with terminal illnesses, dying is something that is expected and planned for over a period of weeks to months, or even years. For other patients, particularly those with acute illnesses, death can be prevented with hospitalization and aggressive treatment. To date, efforts to reduce preventable in-hospital mortality have focused on improving treatments and care delivery, and efforts to reduce non-preventable mortality have focused on supporting patient preferences to die at home and attempting to reduce health care costs in the inpatient setting. Early identification of patients at high risk of in-hospital mortality may improve clinical and operational decision-making and improve outcomes for these patients.

To assist efforts to improve the quality and safety of care at Duke Health, we partnered with the DUHS Mortality Review Team to build a machine learning model to predict in-hospital mortality, run at the time of admission to the hospital for all adult patients. We carefully designed the

TEAM

Nathan Brajer, Brian Cozzi, MS, Michael Gao, Marshall Nichols, MS, Mike Revoir, Suresh Balu, MBA, Joseph Futoma, PhD, Cara O'Brien, MD, Chet Patel, MD, Jonathan Bae, MD, Pooh Setji, MD, Adrian Hernandez, MD, MHS, Mark Sendak, MD, MPP

model to be implementable on a system-level, choosing an approach that was not disease specific, used accessible computational methods, and relied on data readily available in EHRs. We retrospectively evaluated model performance at DUH, DRH, and DRAH, and completed the evaluation of a machine-learning model to predict in-hospital mortality with highly encouraging results that we plan to publish. We created a model facts sheet, similar to a drug label, that clearly explains the “indications” and “contraindications” for model use and provides other important information for clinical and operational leaders. Lastly, we prototyped initial workflows to test, established baseline metrics, and built a dashboard to display patient risk scores to support initial workflows. We plan to evaluate different workflows across DUH, DRH, and DRAH to assess the impact on patient outcomes, and look forward to sharing the results. 💡



“My time with DIHI has been an incredible learning experience. Through working directly with the clinical leaders, statisticians, software developers, and front-line staff, I’ve learned to speak different “languages”—clinical, technical, and operational—that have enabled me to work more effectively in multidisciplinary teams doing new and challenging work.”

Nathan Brajer

I’m very thankful to have had the opportunity to be a part of the DIHI team over the past three years. After my second year of medical school, I joined the team for my first “3rd year” of medical school, and continued to work with DIHI in various capacities over my 2nd and 3rd “3rd years” as I completed an MBA at Fuqua.

During my first year at DIHI, I built a CKD Population Health economic model to help healthcare organizations better understand major cost drivers in their CKD population, and to forecast the financial impact of more effectively deploying evidence based-interventions over time. During that year, I also contributed to the early stages of a project to develop a machine learning model to predict the onset of sepsis in the hospital, and integrate this model into a clinical workflow designed to improve the delivery of evidence-based interventions for these patients. During my 2nd year at DIHI, most of my time was devoted to my MBA coursework, but DIHI was incredibly supportive in helping identify real problems the health system faces that I could help solve by applying what I was learning in school. I applied what I learned in my finance and operations courses to help service line leaders understand the impact an eConsults service model would have on department finances and wait times for outpatient appointments.

During my 3rd year at DIHI, I completed my official medical school thesis while finishing my MBA coursework. My main project was developing, implementing, and evaluating a machine learning model designed to predict in-hospital mortality at the time of admission. I also contributed to various other projects related to lowering mortality rates, including building a mortality review dashboard for operational leaders, conducting service line and patient sub-population mortality analyses, and developing methods for improving the quality of out-of-hospital death outcomes data used for operational initiatives and clinical research.

My time with DIHI has been an incredible learning experience. Through working directly with the clinical leaders, statisticians, software developers, and front-line staff, I’ve learned to speak different “languages”—clinical, technical, and operational—that have enabled me to work more effectively in multidisciplinary teams doing new and challenging work. I’ve learned basic coding, and developed the skills to explore and analyze complex EHR data and to share insights in a clear and actionable way. I’ve learned about the massive barriers associated with integrating new technologies into clinical care, how to anticipate problems, how to ask the right questions, and how to test critical assumptions early on. Beyond this, I’ve learned about challenges facing all teams doing innovative work in healthcare, and how good teams meet challenges.

Working with DIHI has been highly influential on my future career aspirations. One day, as a clinician, I hope to lead efforts at the intersection of clinical medicine, technology development, and business model innovation, with the aim of driving system-level improvements in how we help people achieve their health goals. In the short-term, I’m looking forward to pursuing residency training with the ability to view healthcare delivery through different lenses, and hopefully continuing to contribute to innovative health system work as a resident!



"WE IDENTIFIED THAT MOST AGGRESSIVE CARE [AT THE END OF LIFE] WAS DUE TO OVER ADMISSION OF PATIENTS (AS OPPOSED TO ED VISITS OR CHEMOTHERAPY TREATMENTS.)"

Angela Lowenstern MD

Project Normal Echo

UTILIZATION OF MACHINE LEARNING TO READ TRANSTHORACIC ECHOCARDIOGRAMS

Transthoracic echocardiogram (TTE) studies are widely used as non-invasive evaluations of cardiac function and structural heart disease. The volume of studies completed at Duke has been increasing over time with over 22,000 studies completed in 2017 alone. Part of this growth is represented by multiple TTE studies on the same patient during a single admission in the era of bundled care. The current process for obtaining and evaluating TTE images at Duke, and many other large centers, consists of a sonographer procuring images and then completing a preliminary report. An attending echocardiographer then evaluates this report, along with the corresponding images. Edits to the report are made, as needed, and then the finalized results are uploaded to the electronic health record. Subsequently, the ordering clinician can review the information and make clinical decisions based on the results. Although average scan to result time is currently 4 hours at DUHS and nearly 100 TTEs are completed on a single weekday, approximately 1 in 5 studies are not completed within 24 hours of being ordered. This sometimes results in

TEAM

Angela Lowenstern, MD, Michael Gao, MS, Rui Wang, MS, Carter Davis, BS, RDCS, Jayne Cleve, BS, RDCS, Alicia Armour, MA, RDCS, Mark Sendak, MD, MPP, Suresh Balu, MBA, Ricardo Henao, PhD, Sreekanth Vemulapalli, MD

prolonged hospital stay, especially over the weekend, for patients who cannot be discharged prior to the completion of an echocardiogram. If even 5 minutes of time spent by the sonographer were saved by automation of the TTE preliminary report, it is estimated that this would lead to an additional 60 hours of useable time by sonographers each week, during which additional studies could be completed. In addition to improved efficiency, automated interpretation would also help to reduce interobserver variability. Currently, even among core-laboratory trained echocardiographic readers, there is up to 25% variability in estimated ejection fraction. Given that multiple pharmacologic and device therapy decisions are made based on ejection

fraction, this variability has significant implications for cardiac care.

In this project, in an effort to expedite results and reduce overall cost, we sought to develop and validate a computer algorithm to correctly estimate left ventricular ejection fraction (LVEF) as an initial step toward a fully automated echocardiogram evaluation.

OBJECTIVES

We were seeking to understand the causes of over-aggressive care at the end of life. We identified that most aggressive care was due to over admission of patients (as opposed to ED visits or chemotherapy treatments).

AIM 1

Utilize machine learning methods to evaluate LV performance using TTE images. Overall LV performance will be determined using multiple aspects of echocardiographic data with LV segmentation in order to accurately estimate LVEF within 5-10% of a visual echocardiographic read.

AIM 2

Reduce average time from TTE image acquisition to preliminary report generation and final TTE interpretation availability for ongoing patient clinical care.

SOLUTION AND OUTCOMES

Identification of TTE studies

We identified 1,074 TTE studies from the PROMISE study and an initial set of 3,000 Duke TTEs with at least moderate image quality to begin model development. PROMISE TTEs have been core lab adjudicated, which provides a gold standard echocardiographic interpretation by two independent cardiologists. Additionally, use of these images, which are obtained from institutions across the United States, improves the potential generalizability of our final product. The Duke TTEs give a large number of studies from a diverse population of patients to utilize for training the machine learning algorithm.

Creation of a durable solution for image transfer

Working with individuals from the Heart Center, DHTS and DCRI IT, we developed a semi-automated process by which Duke TTE studies are transferred from Phillips PACS to a secure PACE environment. In a step-wise manner, studies are identified in the Phillips PACS server based on study ID. Each study is then transferred to the

vendor neutral archive (VNA), a secure intermediate step where studies can be stored and easily accessible. Upon availability, TTEs are then transferred into the secure PACE environment where the model development can occur. We intentionally created a system that is not only applicable for our project but that could also be utilized for future research at Duke. This same pipeline of transfer can be used for any studies housed in Phillips PACS, including TTEs and angiograms from the Duke Cath Lab. During our study period, we were able to successfully transfer 3,000 TTEs to the VNA with over 1,000 moved into PACE for model development.

Echocardiographic view identification

As a first step toward model development, we used machine learning to correctly identify different echocardiographic views for analysis, per previously published methods.¹ The views included for the LVEF estimation were parasternal short axis, AP 2 chamber, AP 3 chamber and AP 4 chamber. Our preliminary image modeling approach provided image frame level classification with a 98% accuracy and DICOM level accuracy at 80% (Figure 1).

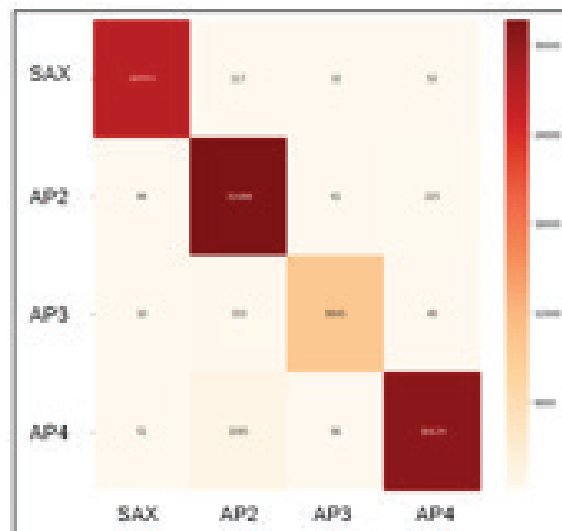


Figure 1

Segmentation of the Left Ventricle and Left Atrium

In order to build the machine learning algorithm for LVEF estimation, we started with segmentation of the LV and LA. In this process, trained cardiac sonographers trace the endomyocardial border of the left ventricular and left atrial cavities (Figure 2). These segmentation images can then be used for training of the computer model for LVEF estimation. At the time of this report, we have

Project Normal Echo, continued

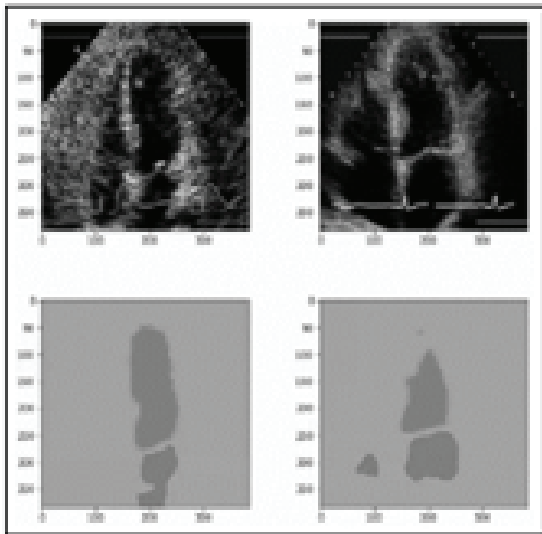


Figure 2

completed segmentation of 23 PROMISE studies. Each segmented study includes four views (short axis, AP2, AP3 and AP4) with three frames per view (systole, mid and diastole). This totals 276 frames successfully segmented.

LVEF Estimation

We began LVEF estimation by using a recently published algorithm from UCSF¹ to try to estimate LVEF using PROMISE study echocardiograms. However, while this algorithm worked well for the view identification above, the performance of LVEF estimation was less robust with many LVEF estimates of zero, suggesting a potential issue with algorithm generalizability. Following this, we have begun initial estimation of LVEF using a preliminary machine learning algorithm which was developed using data from our segmentation work. This algorithm will continue to be updated as ongoing segmentation work is completed.

CONCLUSIONS AND FUTURE DIRECTIONS

During the time of our DIHI award, we have been able to: 1) Create a durable solution for transfer of images from the Phillips PACS server to the secure PACE environment to allow for image processing; 2) Use machine learning to identify the correct echocardiographic view with 98% frame level classification accuracy; 3) Fully segment the LV and LA for 276 unique frames from the PROMISE study and 4) Begin development of a computer algorithm, utilizing machine learning techniques, to accurately estimate LVEF.

Our immediate next steps include completion of the computer algorithm and validation of this algorithm using both PROMISE and Duke echocardiographic studies. Following model validation, we plan to implement use of the model in the Duke North echo lab through an API in the LUMEDX reporting system. After this successful implementation, we would plan subsequent expansion to other parts of the Duke Health System. Eventually, the algorithm has the potential to be utilized at outside institutions. By using PROMISE studies, which were obtained at numerous institutions, as well as the large number of potential Duke studies, we believe that our model will have a generalizability that is not possible using other data sources.

Beyond implementation, we plan to continue model development which will focus on additional aspects of the TTE study, including valvular heart disease and pericardial disease, as a step toward our overarching goal of the ability for a computer algorithm to identify a fully normal TTE study.

From an output perspective, we plan to file for intellectual property rights upon model validation. We will also submit our work as an abstract for presentation at a national cardiovascular meeting and plan to submit manuscripts to peer reviewed journals which will detail the model development, model validation and implementation phases of our project. 💡

¹Zhang, Jeffrey, et al. "Fully automated echocardiogram interpretation in clinical practice: feasibility and diagnostic accuracy." *Circulation* 138.16 (2018): 1623-1635.

"BEYOND IMPLEMENTATION, WE PLAN TO CONTINUE MODEL DEVELOPMENT WHICH WILL FOCUS ON ADDITIONAL ASPECTS OF THE TTE STUDY, INCLUDING VALVULAR HEART DISEASE AND PERICARDIAL DISEASE, AS A STEP TOWARD OUR OVERARCHING GOAL OF THE ABILITY FOR A COMPUTER ALGORITHM TO IDENTIFY A FULLY NORMAL TTE STUDY"

Angela Lowenstern MD



“This pipeline has allowed us to complete projects at a much faster rate and allowed us to focus on the truly difficult parts of innovation in healthcare—implementation and workflow design.”

Michael Gao, Data Scientist

Data Pipeline

At the Duke Institute for Health Innovation, we are excited by the prospect of putting machine learning to practice in medicine. When we first began developing machine learning solutions, machine learning in healthcare was in its infancy. However, we felt then—as we do now—that all of the pieces were in place to allow data-driven approaches to transform medicine. It seems like a forgone conclusion that by leveraging the vast amount of data that is present in the medical record, machine learning can aid physicians in detecting disease earlier, informing treatment protocols, diagnosing, and identifying patients who need specialized care.

However, our initial efforts were anything but streamlined. We quickly realized that any machine learning solution was gated by access to data. During early projects, it would take upwards of 6 months or more to get access and access the data required. Given our short pilots, it was immediately clear that until we had a reliable and timely way of accessing clean medical record data, our projects would continue to rate limited.

Even once we had the data, it was evident that there was much more work to be done before we could deliver robust machine-learning based solutions. The electronic health record data we work with is about as clean as my mother thinks I am. Many of our early efforts involved going through the process of resolving different names for the same clinical concept, harmonizing units for lab tests, and similarly engaging work. Our clinical partners, who we asked to help with this effort, seemed delighted by the iterative and manual nature of the work.

As we began curating this information for use in future projects, we also began receiving more and more project proposals having to do with machine learning. We soon realized that in order to keep up with the increasing volume of data needs, we needed a scalable way to work with data, which led us to build the DIHI Data Pipeline.

At its core, the DIHI pipeline allows users to work with clean and reproducible data. By clean, we mean that rather than grouping raw data elements over and over again for different projects, we can house all of this knowledge in the same place. Lab test result units are converted to ensure consistency across the same analyte. Existing references for methods to group ICD codes, medication therapeutic classes, procedures, and other data fields should be easily accessible. This both reduces the time it takes to go from raw data to a dataset ready for analysis and the amount of redundancy across projects and groups at Duke Health. In addition, we ensure that queries to the system are reproducible where possible so that analysis performed today should be able to be consistent two years from now. In building the pipeline, we leveraged technologies and best practices that are used and developed at major tech companies such as Google, Uber, and AirBnB and are continuing to add features as we service new use cases.

This pipeline has allowed us to complete projects at a much faster rate and allowed us to focus on the truly difficult parts of innovation in healthcare—implementation and workflow design. We believe that much of our success is in part due to this pipeline and the team that helped to design and build it. As we continued to tackle more difficult challenges, we expect that the pipeline will continue to accelerate and enable innovation in healthcare at Duke and beyond.

ePRO in Cancer Care

OPTIMIZING PATIENT-REPORTED OUTCOMES DATA AND WORKFLOWS IN MAESTROCARE

This pilot project aimed to demonstrate the feasibility and utility of integrating electronic patient-reported outcomes (ePROs) into the existing Epic electronic health record for use in outpatient cancer care.

In cancer care, patients' symptoms can go undetected up to half of the time in clinic visits.¹ To fill this gap, quality of life issues and symptoms can be tracked systematically through patient-reported outcomes, whereby patients directly report on their experiences using validated questionnaires. Use of electronic PROs has been shown to improve patient quality of life, reduce trips to the emergency department and lengthen survival.² Despite the proven benefits of ePROs, they have not been widely incorporated into routine cancer care through the existing electronic medical records (EMRs).

SOLUTION AND OUTCOMES

During this pilot project, a clinically-useful PRO, the 10-question ESAS symptom screener, was integrated into the existing Epic EMR at three outpatient oncology clinics. Patients completed the questionnaire prior to their visit using the MyChart patient portal. A visualization system was created to allow for rapid assessment of patient symptoms and symptom trends in the "synopsis" view. The ePRO data was also made available in a SmartPhrase that enabled rapid inclusion in the clinical note. Site visits were conducted to optimize clinical workflow. Several patient engagement strategies were employed including automated generic reminders and personalized messages from the clinical team through the online patient portal, MyChart, phone calls and welcome tablets at patient check-in.

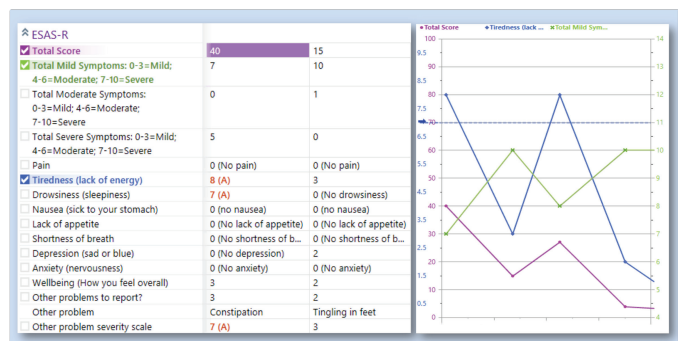
The integration of ePROs into outpatient oncology clinics is best broken down into three components for analysis: 1) technical implementation, 2) patient engagement, and 3) workflow optimization. The technical implementation proceeded more rapidly than initially estimated. The existing ePRO tool in Epic allowed for simple integration of the ESAS questionnaire into the provider and patient-facing systems. Initial patient engagement was low, despite automated MyChart reminders about the ePRO questionnaire. To improve engagement, rapid A/B testing was done to compare phone call reminders

TEAM

Thomas W. LeBlanc, MD, MA, Kris Herring, PhD, Bridget Koontz, MD, PhD, Yousuf Zafar, MD, MHS, Heather Rosett, Will Ratliff, MBA

against MyChart messages from the clinical team. Both testing strategies increased ePRO survey response rates equally. Despite these reminders, questionnaire response rates remained low and welcome tablets were introduced at the time of check-in to make this system more widely available to patients. The clinical workflow was analyzed during site visits. The key barrier to efficient use of the ePRO in clinics was the time required to file patient data before it could be incorporated in the clinical note. This barrier was resolved in a recent Epic upgrade. In conclusion, this pilot project demonstrated that technical implementation of ePROs within the Epic system is straight-forward technically, but strategies for patient engagement and clinical workflow optimization are required for successful integration.

This work was presented as a poster presentation at the AMIA 2019 Clinical Informatics Conference held in Atlanta, GA. A paper featuring learning from implementation and our results is planned. 💡



USE OF ELECTRONIC PROS HAS BEEN SHOWN TO IMPROVE PATIENT QUALITY OF LIFE, REDUCE TRIPS TO THE EMERGENCY DEPARTMENT AND LENGTHEN SURVIVAL.



"This year has given me hands-on experience dealing with the complexities and potential of harnessing healthcare data to promote change."

Heather Rosett

Innovation in healthcare encompasses a vast range of initiatives led by teams dedicated to improving patients' experiences and outcomes. These advances all start with identification of a problem, often through clinical experience and careful analysis of the vast amount of data being collected in the healthcare system. In my year as a DIHI scholar, I worked on projects to address many problems including: cancer patients' symptoms often go unaddressed; unnecessary labs can be costly to patients; early readmission to the hospital is harmful to patients. Each of these projects started with data and then we built solutions that married technology and clinical care to help our patients.

In my primary projects, I had the pleasure of working with Dr. Thomas LeBlanc to integrate patient-reported outcomes (PROs) into the electronic health record (EHR) in cancer clinics across Duke. This project stemmed from data that illustrated how many patients' symptoms go unaddressed in increasingly short clinical visits. This can lead to many unintended consequences such as emergency department visits and shorter life expectancy for cancer patients. Using the capabilities of the existing EHR, we piloted a project utilizing PROs to systematically captured patients' symptoms ahead of the clinical visit to better enable clinicians see trends (figure 1) and address all of their patients' chief concerns. Success of this project hinged on optimizing the clinical workflow and learning how to best engage patients through technology, which are key components of many efficacious innovations in our field.

To shape the future of patient care, clinicians in our evolving environment need to be increasingly confident in working with data and technology. This year has given me hands-on experience dealing with the complexities and potential of harnessing healthcare data to promote change. These skills can be translated into every specialty, but I'll specifically be applying them to a career in obstetrics and gynecology.

Integrating Electronic Patient Reported Outcomes Into Clinical Workflows in the Epic® Electronic Health Record

Heather A. Rosett; Kris Herring, PhD; William Ratliff, MBA; Bridget F. Koontz, MD; S. Yousef Zafar, MD, MHS; Thomas W. LeBlanc, MD, MA, MHS;

BACKGROUND

Patients with cancer experience a wide range of symptoms, which can go undetected up to 50% of the time in clinic.¹

Electronic patient-reported outcomes (ePROs) can help fill this gap by allowing patients to directly report on their own experiences in a systematic way.

Use of ePROs can improve quality of life, reduce trips to the emergency department and lengthen survival.²

The problem: Despite proven benefits, ePROs are not widely integrated into clinical care.

FIGURE 1: MyChart® to the Clinical Note

1. ePRO Survey for Patients

RESULTS

Feasible: ePRO questionnaire integrated into patient and provider facing Epic® platforms and launched in three months

Barriers:

- Clinical workflow initially complex
- Low patient engagement

↓

OBJECTIVES

Demonstrate the feasibility and utility of integrating ePROs the existing Epic® electronic health record (EHR)

Promote a more proactive system of symptom management

FIGURE 2: ePRO Response Rates

% of Surveys Answered (Across MyChart Accounts Only)
% of Surveys Completed

CONCLUSION

Technical implementation

Epic's built-in ePRO tool is quick to customize and activate

Clinical workflow optimization

Successes:

- SmartPhrase for clinical note
- Symptom trends over time

Barrier:

- Time required for clinicians to "file" patient data

• Solution: Epic® 2018 upgrade streamlined dataflow

Patient engagement

Barrier:

- Low response rates to ePRO questionnaire through MyChart®

Solutions:

- Clinicians review results with patients during clinic visit
- PDSA cycles with different patient engagement strategies

↓

PILOT DESIGN

Selected validated ePRO questionnaire: ESAS-r³

Partnered with internal technology team to activate built-in Epic® ePRO tool

Launched in three outpatient oncology clinics: hematology, gastrointestinal oncology and radiation oncology

Data Flow:

1. Patients complete ePRO questionnaire in the MyChart® patient portal
2. Clinicians view patient generated data in "flowsheet" or "synopsis" while preparing for and during patient visit
3. SmartPhrase used to include ePRO data in clinical documentation

FIGURE 3: PDSA Cycles

3. Patient Generated Data for the Clinical Note

ESAS-r	ESAS-r RUC Flowsheet	Date	Date
Total Score		15	27
Total Mild Symptoms: 0-3=H&L; 4-6=H&Moderate;		3/0	8
0-3=H&L		3	3
Total Moderate Symptoms: 0-3=H&L; 4-6=H&Moderate;		0	2
0-3=H&L		0	2
Total Severe Symptoms: 0-3=H&L; 4-6=H&Moderate;		0	0
0-3=H&L		0	0
Fatigue		3 (No pain)	3 (No pain)
Tiredness (lack of energy)		3 (No symptoms)	3 (No symptoms)
Loss of appetite		3 (No nausea)	3 (No nausea)
Nausea (not to your stomach)		0 (No loss of appetite)	0 (No loss of appetite)
Shortness of breath		0 (No shortness of breath)	0 (No shortness of breath)
Anxiety (nervousness)		2	2
Worrying about your future		2	2
Other problems to report?		2	2
Other problems		Twingling in feet	Neuropathy mainly in left foot and ankle.
Other problem severity scale		3	4
Other problem		Constipation	Tachycardia. Feels beats a little off time table.
Other problem severity scale		3	1
Other problem		1	1
Other problem severity scale		(A) 1	(A) 1

↓

References

1. Pakhomov SV, Jacobsen SJ, Chute CG, et al: Agreement between patient-reported symptoms and their documentation in the medical record. *Am J Manag Care* 14:530-9, 2008.
2. Basch E, Deal AM, Dueck AC, et al: Overall Survival Results of a Trial Assessing Patient-Reported Outcomes for Symptom Monitoring During Routine Cancer Treatment. *JAMA* 318:197-198, 2017.
3. The ESAS-r. Freely available for use. (Wiznabala et al.) *J Pain Symptom Manage* 2011; Buroers et al. *J Palliat Care* 1991.

Questions?
heather.rosett@duke.edu

Duke Institute for Health Innovation

¹ Pakhomov SV, Jacobsen SJ, Chute CG, et al: Agreement between patient-reported symptoms and their documentation in the medical record. *Am J Manag Care* 14:530-9, 2008.

² Basch E, Deal AM, Dueck AC, et al: Overall Survival Results of a Trial Assessing Patient-Reported Outcomes for Symptom Monitoring During Routine Cancer Treatment. *JAMA* 318:197-198, 2017.

2019 Impact Report

31

Innovation Jam: Empowering diverse innovators to propel their ideas forward

For the past five years, since 2015, DIHI has hosted Innovation Jam, a pitch program for innovators across the Duke community. Inspired by NBC's *Shark Tank*, Innovation Jam affords innovators the opportunity to pitch their health-related ideas to Duke investors. Deans, department chairs, division chiefs, and institutional leaders across disciplines have come together over the years to provide valuable feedback and vital support to emerging health innovations. DIHI has worked alongside innovators to present 26 pitches with Duke intellectual property at Innovation Jam events since 2015. As a result, \$395,000 Duke dollars have been awarded in the form of investments in emerging devices, diagnostics, and digital therapeutics. Just as importantly, Innovation Jam provides innovators with institutional support, mentorship, and vital feedback to help shape and propel their novel innovations forward. Many innovators have formed companies, secured investments from outside sources, and continued to contribute to Duke's innovation ecosystem.

The growth of Innovation Jam over the years and the impact it has made in the Duke community has been exciting and I look forward to seeing the event continue to grow and empower the next generation of healthcare leaders.

One of the most powerful components of Innovation Jam is its collaborative energy. Innovation Jam brings together diverse perspectives and expertise to strengthen the ideas we put forth on Jam day. DIHI has partnered with a team of experts across Duke's campus to provide pitch preparation and coaching to Innovation Jam finalists. The Office of Licensing & Ventures has developed market scans for finalists; Fuqua students have engaged with innovators to develop business plans and milestones; a panel of evaluators from Pratt, Nicholas, Nursing, Medicine, and others have contributed their time to coach innovators and help prepare pitches.

Further, our team of investors represents a cross-disciplinary group of Duke leaders. Their support has been instrumental in growing the culture of innovation and entrepreneurship at Duke. The engagement we've received from our team of investors, not only during the Innovation Jam, but also throughout the year, is invaluable to cultivating the culture of innovation and entrepreneurship at Duke.

We are grateful to the innovators, evaluators, investors, students, and many more who have contributed to Innovation Jam. Thank you. Together, we can continue to innovate and solve some of healthcare's greatest challenges.



"DIHI has worked alongside innovators to present 26 pitches with Duke intellectual property at Innovation Jam events since 2015. As a result, \$395,000 Duke dollars have been awarded in the form of investments in emerging devices, diagnostics, and digital therapeutics."

Krista Whalen



Suresh Balu, Marion Broome



Bill Fulkerson



Mercy Asiedu, Libby Dotson



Nan Jokerst, Ben LaRiviere



Ebony Boulware, Manesh Patel, Suresh Balu



Jon Fjeld



The Calla Imaging Team

DUKE HEALTH INNOVATION JAM IS AN OPPORTUNITY FOR DUKE'S BRIGHTEST MINDS TO PITCH THEIR HEALTH-RELATED IDEAS TO DUKE INVESTORS.

Code Blue mobile app

DIHI, in partnership with The Duke Heart Center, developed an iPad app to be used to document the activities during a Code Blue. Code Blue is a high-intensity emergency scenario in which a patient is in cardiac arrest and requires a team of clinicians to respond quickly to being efforts to rescue the patient.

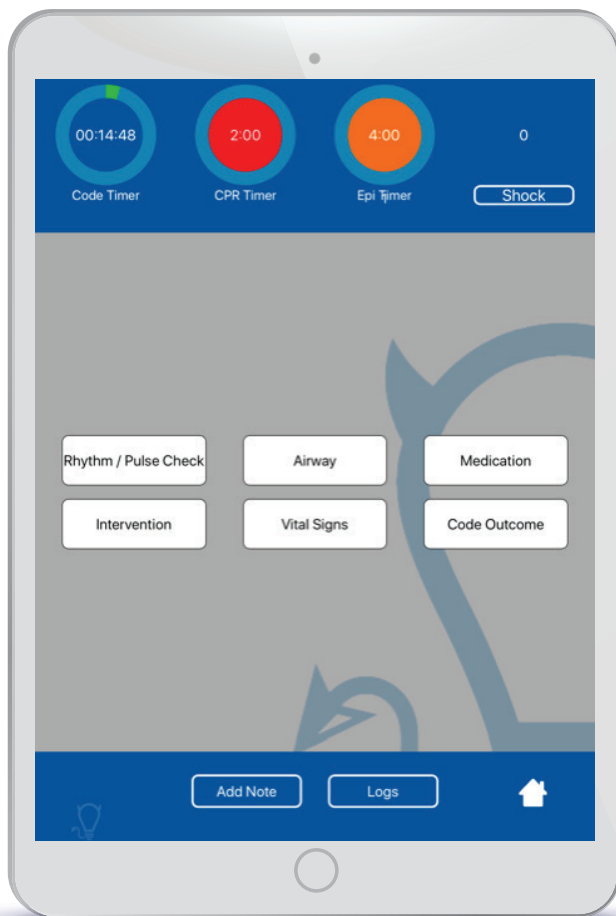
Documentation previously was performed by a nurse using a code sheet and pen or pencil. The document was large and not intuitive even for the skilled staff. Since Code Blues are fast-paced and occur infrequently, clinicians are often unfamiliar with the documentation and thus items were duplicated or omitted. With the creation of the Code Blue iPad app, the teams' goal was to create a tool that would be intuitive, easy to use and lessen any documentation issues during the Code Blue.

TEAM

Corey Miller, RN

Jamie Daniel

Corey Miller from the Heart Center and Jamie Daniel from DIHI have spent hours going over each detail and running mock scenarios through the application to prepare it for user testing and piloting. Without the expertise of the two teams this application couldn't have been accomplished. A true collaborative project created an amazing outcome. 💡





VOICES OF DUKE HEALTH INVITES HEALTHCARE PROVIDERS, STAFF, STUDENTS, TRAINEES, PATIENTS, AND VISITORS TO HAVE CONVERSATIONS ABOUT WHAT IS MEANINGFUL IN YOUR LIVES, WORK, AND RELATIONSHIPS.

Voices of Duke Health



TEAM

Karishma Sriram, Susannah Roberson, Anton Zuiker, MA, Jonathan Bae, MD, William Dawson, Mark Simonsen, Jack Fleischman, Dennis Mathias, Krista Whalen

Our project aimed to facilitate and record meaningful conversations. We shared those voices in 15 episodes of a publicly available podcast. Conversation participants and listeners alike reported appreciation for the opportunity to listen and to be listened to. We believe this successful pilot reflects an effective approach to addressing provider burnout and promoting a culture of well-being among the Duke Health workforce. We aim to continue this work, and have crafted a vision for the future of Voices of Duke Health.

Voices of Duke Health invites healthcare providers, staff, students, trainees, patients, and visitors to have conversations about what is meaningful in your

lives, work, and relationships. Our podcast features your conversations. Learn more and listen at www.listeningbooth.info.

Voices of Duke Health is an initiative of the Department of Medicine and the Duke Health Office for Patient Safety and Clinical Quality.

Problem we sought to solve

Our proposed pilot aimed to address a deceptively simple problem: a large and sprawling organization such as Duke Health can never listen enough to its people and patients. But small, simple interventions can move us in the right direction. We proposed an initiative built around themes of listening, conversation, and storytelling that could help build resilience and well-being among the workforce, as well as introduce a novel patient interaction.

Voices of Duke Health, continued

The 2016 Duke Health strategic planning framework, *Advancing Health Together*, identified a goal of sustaining Duke as a “place where everyone thrives and is valued.” The annual work culture survey has indicated high levels of employee satisfaction, but feelings of stress and burnout are evident, and the institution is committing resources to finding effective ways to strengthen resiliency. It seems to be early days for these efforts, but it is clear we must find ways to communicate success stories and hear from colleagues who have found effective ways to muscle through the stresses of working in health care.

It is good to listen to people tell their stories, and to hear others talk about the experiences that drive medicine and science forward. We believe it is important to facilitate and record these stories and to use them to build the resiliency of the workforce and the satisfaction of our patients. We want people—staff and visitor alike—to leave Duke Health thinking, “They listened to me.”

SOLUTION

Our solution was to propose the Voices of Duke Health listening booth to provide a physical place where Duke Health makes explicit a commitment to listen. In the listening booth, we aimed to provide a dedicated space where patients, family members, visitors, students, trainees, and medical professionals could schedule time for facilitated conversations.

We wanted to record these conversations and share the voices, stories, conversations, and lessons in a publicly available series of audio episodes (a podcast). This podcast would thereby demonstrate how the institution listens to our people and celebrates their experiences, expertise, and insights. We hoped the podcast episodes would reflect inter-professional connections and a culture of professionalism and teamwork as well as highlight positive emotions and healthy habits.

Our goal with this project was to show patients, their families, and our colleagues that we value all who come to Duke and appreciate their life experiences.

We borrowed the waiting room within the Duke Medicine Pavilion Patient Resource Center to create the Voices of Duke Health listening booth. In there, we set up a temporary recording studio with a table and chairs, quality microphones and recording equipment, and materials to inspire meaningful conversations. (See photos above.) We recorded 25 conversations, from which Susannah and Karishma produced 15 engaging podcast episodes.

We also took our mobile recording cart into the medical center hallways and to various department and alumni events. For this, we asked a “question of the day” (along with the backup question “For what are you most grateful?”). At one of the first of these, we recorded a heartfelt response from the mother of a pediatric patient, and that audio from Shawn Burrow was one of our most effective examples of the power of this project. While these mobile-recording events did give the Voices of Duke Health project exposure, we found that the impromptu nature of a hallway interview gave mostly superficial answers.

To promote Voices of Duke Health, we produced posters, stickers, pins, window treatment, and stress balls. Susannah and Karishma managed social media accounts (@DukeVoices) on Twitter and Instagram, and we used the @DukeMedicine and our personal Twitter accounts to highlight the podcast.

By the Numbers

Voices recorded in listening booth conversations and mobile recording cart events	150
Conversations in the listening booth	25
Voices in listening booth conversations	57
Mobile recording cart events	9
Voices recorded at mobile recording cart events	93
Number of podcast episodes	15
Total listens as of April 25, 2019	7001

OUTCOMES AND IMPACT

We recorded 25 conversations; all of the participants provided their consent for use of their recordings for a public podcast.

We produced 15 episodes for the podcast and published the episodes with the online platform SoundCloud; the podcast was available through most podcast directories. Each week, we posted a one-minute teaser about the conversation to be featured that week. The full episode was published on Thursday afternoons, with an episode-specific page on the website that included the embedded SoundCloud player, a full transcript, and additional resources related to Duke resources or national health advocacy groups (CPR, strokes, diabetes).



“AS THE HOST OF VOICES OF DUKE HEALTH, I’VE HAD MANY CONVERSATIONS WITH INDIVIDUALS—OFTEN PRAISING OUR TEAM’S HARD WORK ON THIS PODCAST. HOWEVER, ONE CONVERSATION WITH A GROUP OF MEDICAL TRAINEES INTRIGUED ME. THE GROUP STARTED OUT BY COMPLIMENTING OUR PROJECT, HOWEVER, THEY WENT ON TO SAY THAT, IN PARTICULAR, “THE GAUNTLETS” EPISODE ACTUALLY AFFECTED THE WAY THEY COMMUNICATED WITH INDIVIDUALS WHO HAD LOST A FAMILY MEMBER. RATHER THAN SAYING “I’M SORRY,” THEY NOTED THAT THE PODCAST MADE THEM CHANGE THE WAY THEY REACTED—THEY CHOSE INSTEAD TO SIT BY THE PERSON IN SILENCE, OR TOLD THEM THAT THEY KNOW IT MUST BE TOUGH AND THEY ARE HERE FOR THEM. THEY WERE CONSCIOUSLY APPLYING THE LESSONS THAT THEY LEARNED FROM DR. GALANOS’S STORY TO THEIR LIVES AND THE PEOPLE AROUND THEM”

Karishma Sriram



FEEDBACK

We asked participants in the listening booth to complete a post-conversation feedback form to assess their state of well-being and burnout and how their feelings after the listening booth session. A quarter of respondents indicated feelings of burnout, reflecting that participants were selected for their awareness and strategies toward burnout. All respondents expressed satisfaction with their listening-booth conversation. See below for the full feedback report.

Additionally, we collected feedback through email, social media, and our own conversations. Episode 10 was a particularly powerful episode, and we received many comments, including these messages:

Dr. G—I am sitting here in a cafe Heathrow airport in London at 6 AM travelling home from a medical mission in Rwanda, tears rolling down my face after listening to the podcast. Thank you for sharing your thoughts on the grief process after your experience. — Martin Ingi Sigurðsson, MD (SICU fellow 2017-2018)

Team—The podcast is amazing. Can’t tell you how much I have enjoyed listening...I listened to Dr. G’s story yesterday while driving home from rounding. I had to pull over it was so impactful. Please keep up the work.

— Matthew Sparks, MD

OTHER OUTPUTS

During the project, we fielded requests for assistance and/or guidance from Duke colleagues and units working on audio projects or interested in interviewing event attendees. We offered our audio production services to these groups:

- Department of Obstetrics and Gynecology for the alumni gala
- School of Medicine dean’s office for the From One Duke to Another podcast
- School of Medicine for the annual Medical Alumni Weekend
- Healthy Duke Fulfillment and Purpose working group
- Internal Medicine Residency Program and Durham VA Medical Center

Laura Caputo, MD, came to us for guidance on a podcast project she was starting at the Durham VA Medical Center. We offered our production services, which allowed Dr. Caputo to focus her efforts on recruiting her colleagues to participate. “Susannah is incredibly skilled in modern media, and her expertise has taken our podcast project to a level of professionalism that



“Above all, DIHI has taught me that even in healthcare, there is always room for innovation and for pushing the boundaries.”

we could not have achieved without her. She is both knowledgeable and dependable, and would be an invaluable permanent resource for any public relations department. Additionally, Susannah’s involvement has given the project credibility and increased participation from faculty.”

Our vision: growing Voices of Duke Health into a core resource for other units that wish to use audio storytelling, conversation, and podcasting to reflect their people. Voices of Duke Health began in 2018 as a pilot project to facilitate and record meaningful conversations across Duke Health. Our initial season was a success and shows that the project is an effective approach to addressing provider burnout and promoting a culture of well-being among the Duke Health workforce. We propose to continue this project.

RECOGNITION

Voices of Duke Health was featured in a session at the AAMC Group on Institutional Advancement annual meeting (April 2019) called Best Practices in Digital Storytelling from Around the GIA. We intend to submit the project to the 2020 GIA Awards of Achievement.

Voices of Duke Health was selected as one of the eight winners in the ABIM Foundation’s inaugural Trust Practice Challenge (<https://abimfoundation.org/what-we-do/initiatives/trust-practice-challenge>). Anton has been invited to attend the Foundation’s 2019 Forum, [Re]Building Trust: A Path Forward (August 2019) to present our project in a short plenary meeting entitled “Innovations: Practices That Build Trust.” In addition, the project will be featured in a compendium of noteworthy trust practices. 💡

Karishma Sriram

During my DIHI scholar’s year, I had the incredible opportunity to engage in the intersection of medicine and a variety of disciplines. My primary project was the Voices of Duke Health Listening Booth podcast, for which I was the host. Through this experience, I was able to have vulnerable conversations with members of the Duke Health community from patients to nurses to physicians to some of the most senior administrators. From this experience, I was not only able to hear some of the most inspiring and joyful and painful stories that people in our community experienced, but I was also able to understand the power of humanities in medicine, the power of providing a space to share stories. It was quite the moment to be able to see the solace that people had in sharing their stories in our space, and also hear the listeners relate to the messages and stories that individuals shared on our podcast.

While this was my primary involvement, DIHI also afforded me opportunities to learn about the intersection of data science and medicine through predictive models for cardiogenic shock. I’ve been able to employ my previous coding experience to greatly expand my knowledge of the capabilities of coding. Furthermore, as a DIHI scholar, we were entrenched in discussions surrounding innovation, leadership, management, and health policy both in the context of Duke Health and our nation at large. This opportunity has been invaluable to me as it’s help guide my interests for my future career.

As I approach my fourth year, I plan to apply to a Pediatrics residency to pursue general pediatrics. During my residency and after, I hope to be able to engage in health policy research. As I progress in my career, I also hope to be a part of hospital administration. The background and interests I’ve cultivated during my time at DIHI will be invaluable as I aim to pursue these two areas in my career. DIHI has equipped me with the knowledge and courage to be able to engage with and change both of these arenas.

Above all, DIHI has taught me that even in healthcare, there is always room for innovation and for pushing the boundaries. From what I’ve learned at DIHI, even a single individual (like me!) can instigate this change. While the healthcare system can at times seem rigid in their processes, I think that innovation in healthcare and the necessity for it will become more and more evident and desired.

RFID tracking

SURGICAL INSTRUMENT TRACKING AND OPTIMIZATION OF THE OPERATING ROOM

Operating rooms (ORs) generate both the largest revenue and incur the greatest cost for the hospital. Their efficiency is essential to providing a high level of care at an affordable cost to the patient. Unfortunately, an estimated 78 - 87 percent of instruments in the OR go unused, introducing unnecessary costs in the form of cleaning and processing, delayed surgical operations due to supply mismanagement, increased workload of nursing assistants, and increased instrument wear [1]. For every operation, a balance exists between adequate supply and oversupply. Because the data to describe what instruments are important to an operation does not yet exist, hospitals have erred on the side of oversupply at a significant detriment to efficiency in both cost and time. This is a well-recognized problem; quality improvement studies focusing on instrument supply reduction have been published by multiple institutions [2-10]. Despite the success of these exercises, the implementation effort required across surgical teams retracts from the corresponding cost savings. More efficient methods for gathering instrument usage data are required to enable hospital administrators in maximizing efficiency while ensuring the efficacy of surgical operations.

The focus of this DIHI-funded project was to develop and test a proof-of-concept RFID system that could be

TEAM

Patrick Codd, MD, Ian Hill, MS, Josh Helmkamp, Krista Whalen

integrated into the OR to measure instrument usage autonomously.

SOLUTION AND OUTCOMES

The principal design criterion was to gather data without impacting existing OR workflows. The system uses readers implanted in the operating room to gather proximity data from small, autoclave-compatible RFID tags fixed with surgical marking tape to each instrument. During an operation, tagged instruments enter the field of view of antennas located on the mayo stand and near the surgical site. This data is analyzed and compiled into a list of used instruments. Figure 1 depicts the data log from one craniotomy for tumor operation. The vertical axis has each surgical instrument that was logged throughout the operation. Use instances for each instrument are plotted on a timeline with surgical events as vertical lines. Red use instances correspond to reads from a low-gain whip antenna proximal to the surgical site while blue instances originate from a multiplexed array of low gain mat antennas on the mayo stand. Both

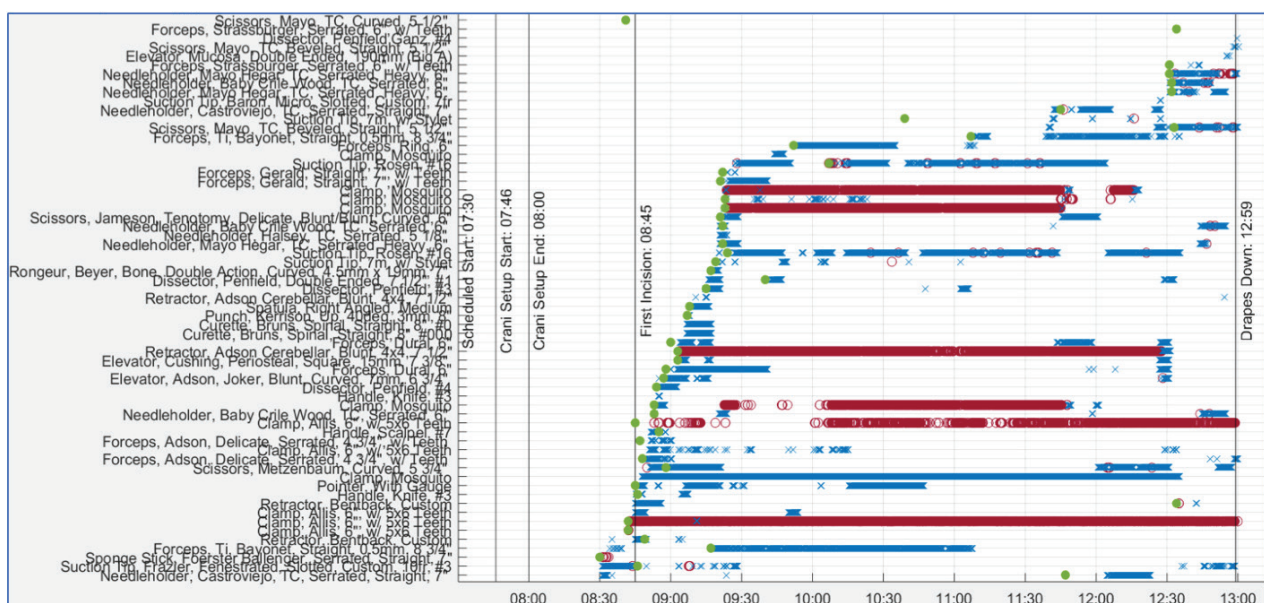


Figure 1: Instrument Use Instances over one Craniotomy for Tumor

RFID tracking, continued

antennas were designed to read instruments within 2-3 feet. Instrument use in each surgery was concurrently observed, and time of first use was manually recorded. The green dots in Figure 1 correspond to manual observation of that instrument first being used. Of the 130 tagged instruments supplied in this operation, only 63 were utilized, supporting the feasibility of supply reduction.

With the ethnographic recording taken as a true measurement of use, both antenna inputs were evaluated as indicators for use over multiple surgeries. The resulting receiver operating characteristic (ROC) plots shown in Figure 2 depict the accuracy of the system over singular surgeries as a function of the system's true positive and false positive read rate. To apply this system to limiting surgical instrument supply, a high true positive rate is favored over a low false positive rate because it ensures all used

instruments are supplied. As surgical tooling variation is obviated by the uniqueness of each case, we recorded instrument usage over four craniotomy for tumor operations and 8 CMC arthroplasties. By combining the output of both mayo and surgical site antennas, the system demonstrates a true positive accuracy rate of 100% and a false positive rate of 81%. Even with an imperfect false positive rate, the system identified a possible supply reduction of 46% in craniotomy for tumor operations and 66% in CMC arthroplasties. In order to quantify how many surgeries are necessary before an accurate master list is identified, we calculated the number of instruments added to the master list for each of the last four craniotomy for tumor operations and the last eight CMC arthroplasties. These are plotted in Figure 3. As expected, the number of instruments added to the master list decays with each follow-on surgery. Although there is not enough clinical use data to define the number of surgeries necessary to predict an accurate preference card, the addition of instruments decays to within one new instrument per surgery in both surgery types before 10 surgeries are monitored.

The RFID system has outlined the need for supply optimization in neurosurgery, orthopedics, plastics, and urology. It has been shown to accurately gather the data required to improve supply efficiency. An average 55% reduction can be achieved with a corresponding savings to the hospital of at least \$220 per surgery. A large hospital system like DUHS stands to save \$14M annually. This project exclusively supported the research of 1 PhD student in engineering and provided research opportunities for 4 medical students. Two publications are currently being drafted, one describing the design and testing of the system, the second analyzing the clinical data gathered.

The concept of instrument tracking with RFID has garnered significant interest across the DUHS community as a result of this project. Follow-on investment from Innovation Jam stakeholders was secured, and studies are currently in design targeting the reorganization of common instrument trays between surgeons based on RFID-gathered data and expansion into transplant surgeries. A company (Mente, Inc) was formed to translate the technology and a license for the technology is currently in negotiation. The team continues to work towards securing further follow-on funding to support the design effort required to scale the technology throughout the Duke Hospital System. 💡

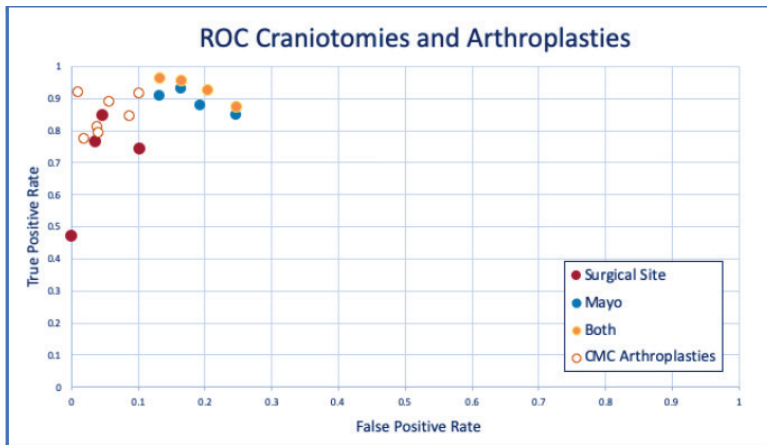


Figure 2: Receiver Operating Characteristic for Antenna Configurations as Indicators for Use

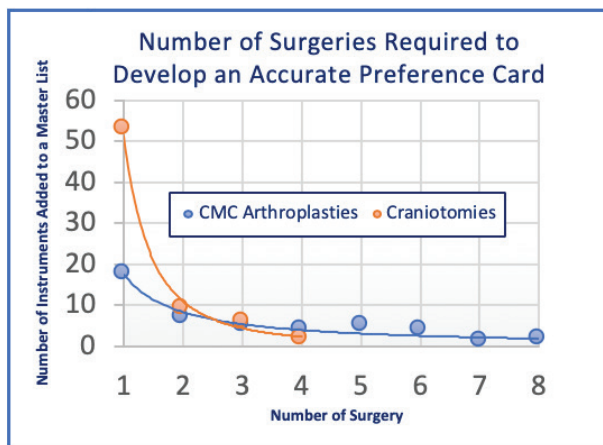


Figure 3: Number of Surgeries to Build an Accurate Preference Card

THE RFID SYSTEM HAS OUTLINED THE NEED FOR SUPPLY OPTIMIZATION IN NEUROSURGERY, ORTHOPEDICS, PLASTICS, AND UROLOGY. IT HAS BEEN SHOWN TO ACCURATELY GATHER THE DATA REQUIRED TO IMPROVE SUPPLY EFFICIENCY.



“To paraphrase Bob Langer—‘throughout the course of education, students are rewarded for having good answers. What really matters, though, is having good questions.’”

Josh Helmkamp

During my scholarship year at DIHI, I had the opportunity to work on several interesting projects. My main project was a pilot of an RFID surgical instrument tracking system in Orthopaedic surgery. As of April 2019, we have been able to collect data on instrument use for nine CMC-Arthroplasty surgeries conducted by two surgeons at the DUHS ambulatory surgery center (ASC). The data generated by our pilot revealed that only 49% of instruments contained in the surgical tray were used during any given CMC-arthroplasty—confirming our hypothesis that surgical instrument oversupply is a significant driver of cost for the ASC. We have also worked on expanding the pilot to other surgical subspecialties—with one case conducted in Urology and plans in the works for an expansion into General Surgery.

Notable side projects include a project on EHR data quality, as well as helping build a 30-day readmission risk model.

Overall, I can confidently say that applying for the DIHI scholarship was a career altering decision. During research year, I aimed for both academic productivity and personal growth. DIHI enabled me to achieve these goals. Throughout the year I learned hard skills such as how to code in python, while the weekly journal club covered wide ranging topics from leadership vs management to business strategy. The DIHI Scholarship provided a special opportunity in which we as students are allowed and expected to apply the skills we acquire throughout the year on real, impactful projects.

To paraphrase Bob Langer—“throughout the course of education, students are rewarded for having good answers. What really matters, though, is having good questions.” My year at DIHI has switched my focus from having the correct answer, to asking the right questions.

- ¹E. W. Stockert and A. Langerman, “Assessing the magnitude and costs of intraoperative inefficiencies attributable to surgical instrument trays,” *J. Am. Coll. Surg.*, vol. 219, no. 4, pp. 646–655, Oct. 2014.
- ²E. Montella et al., “The application of Lean Six Sigma methodology to reduce the risk of healthcare-associated infections in surgery departments,” *Journal of Evaluation in Clinical Practice*, vol. 23, no. 3, pp. 530–539, Jun. 2017.
- ³J. S. Farrelly et al., “Surgical tray optimization as a simple means to decrease perioperative costs,” *Journal of Surgical Research*, vol. 220, pp. 320–326, Dec. 2017.
- ⁴N. Sari, T. Rotter, D. Goodridge, L. Harrison, and L. Kinsman, “An economic analysis of a system wide Lean approach: cost estimations for the implementation of Lean in the Saskatchewan healthcare system for 2012–2014,” *BMC Health Serv Res*, vol. 17, Aug. 2017.
- ⁵F. R. Farrokhi, M. Gunther, B. Williams, and C. C. Blackmore, “Application of Lean Methodology for Improved Quality and Efficiency in Operating Room Instrument Availability,” *J Healthc Qual*, vol. 37, no. 5, pp. 277–286, Oct. 2015.
- ⁶A. John-Baptiste, L. J. Sowerby, C. J. Chin, J. Martin, and B. W. Rotenberg, “Comparing surgical trays with redundant instruments with trays with reduced instruments: a cost analysis,” *CMAJ Open*, vol. 4, no. 3, pp. E404–E408, Aug. 2016.
- ⁷K. H. Cichos, P. L. Linsky, B. Wei, D. J. Minnich, and R. J. Cerfolio, “Cost Savings of Standardization of Thoracic Surgical Instruments: The Process of Lean,” *Ann. Thorac. Surg.*, vol. 104, no. 6, pp. 1889–1895, Dec. 2017.
- ⁸T. J. Wannemuehler, A. N. Elghouche, M. S. Kokoska, C. R. Deig, and B. H. Matt, “Impact of Lean on surgical instrument reduction: Less is more,” *Laryngoscope*, vol. 125, no. 12, pp. 2810–2815, Dec. 2015.
- ⁹D. Lunardini, R. Arington, E. G. Canacari, K. Gamboa, K. Wagner, and K. J. McGuire, “Lean principles to optimize instrument utilization for spine surgery in an academic medical center: an opportunity to standardize, cut costs, and build a culture of improvement,” *Spine*, vol. 39, no. 20, pp. 1714–1717, Sep. 2014.
- ¹⁰M. A. Koyle et al., “Reduction and standardization of surgical instruments in pediatric inguinal hernia repair,” *J Pediatr Urol*, vol. 14, no. 1, pp. 20–24, Feb. 2018.

DIHI Team

DIHI Innovation Staff



William Fulkerson, MD
Executive Director for DIHI
Executive VP for Duke University Health System
and Partnership for School of Medicine



Suresh Balu, MBA
Program Director for DIHI
Associate Dean, Innovation
and Partnership for School of Medicine



Tamika Craig
Staff Assistant



Jamie Daniel
Solutions Architect



Michael Gao
Data Scientist



Bradley Hintze
Data Scientist



Will Knechtle, MBA, MPH
Innovation Program Manager



Marshall Nichols, MS
System & Analytics Manager



Will Ratliff, MBA
Innovation Program Manager



Mike Revoir
Solutions Architect



Mark Sendak, MD, MPP
Clinical Data Scientist



Krista Whalen
Innovation Program Manager

DIHI Innovation Scholars



Kristin Corey



Joshua Helmkamp



Heather Rosett



Morgan Simons



Karishma Sriram



Christelle Tan

DIHI Collaborators



Benjamin Alman, MD



John Anderson, MD



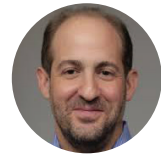
David Attarian, MD



Jon Bae, MD



Armando Bedoya, MD



Hayden Bosworth, PhD



Lynn Bowlby, MD



Nathan Brajer



Stephanie Brinson, FNP



Marion Broome, PhD



Leslie Calihman Alabi,
MA



Rob Califf, MD



Larry Carin, PhD



Maria Carroll



David Casarett, MD



Alex Cho, MD



Patrick Codd, MD



Leslie Collins, PhD



Daniel Costello, MPA



Chris Cox, MD



Connor Davis, MS



Sharron Docherty, PhD



Jeff Ferranti, MD



Jonathan Fischer, MD



Mary Ann Fuchs, DNP, RN



Joe Futoma, PhD



Geoff Ginsberg, MD, PhD



Larry Greenblatt, MD



Brian Griffith, MD



Mitch Heflin, MD



Nicole Heilbron, PhD



Katherine Heller, PhD





Ricardo Henao, PhD



Adrian Hernandez, MD



Kris W Herring, MScM,
PhD



Ian Hill, MS



Fred Johnson, MBA



Schuyler Jones, MD



Aman Kansal



Ravi Karra, MD



Sehj Kashyap



Azalea Kim, MD



Allan Kirk, MD



Mary Klotman, MD



Eugenie Komives, MD



Bridget Koontz, MD



Catherine Kuhn, MD



Walter Kwiatek, MBA,
MSc



Sandhya Lagoo-Deena-
dayalan, MD, PhD



Anthony Lin



Thomas LeBlank, MD



Elizabeth Lorenzi, PhD



Angela Lowenstern, MD



Boyla Mainsah, PhD



Heather Marsteller, MBA



Gary Maslow, MD



Chad Mather, MD



Joseph Mathew, MD,
MBA



Shelley McDonald, PhD



Maggie Meyer, MHA



Paul Newman, MHA



Cara O'Brien, MD



Cameron Olsen



Thomas Owens, MD



Theodore Pappas, MD



Chet Patel, MD



Manesh Patel, MD



Priyesh Patel, MD



Michael Pencina, PhD



Kathryn Pollak, PhD



Eric Poon, MD



Isaretta Riley, MD



Joseph Rogers, MD



Matt Roman, MHA



John Sampson, MD,
PhD, MBA



Dev Sangvai, MD



Sarah Scharber



Pooh Setji, MD



Kevin Shah, MD



Shilpa Shelton, MHA



Tong Shen, MEng



Jessica Sperling, PhD



Sean Sondej, MHA



Madhav Swaminathan,
MD



Geeta Swamy, MD



David Turner, MD



Sreek Vemulapalli, MD



Tracy Wang, MD



Wendy Webster, MBA



Billy Willis, PhD



Yousuf Zafar, MD



Sicong Zhao, MS



Shujin Zhong



Anton Zuiker, MA

 **Duke Institute**
for Health Innovation



 **DukeHealth**

@DukeInnovate
dihi.org