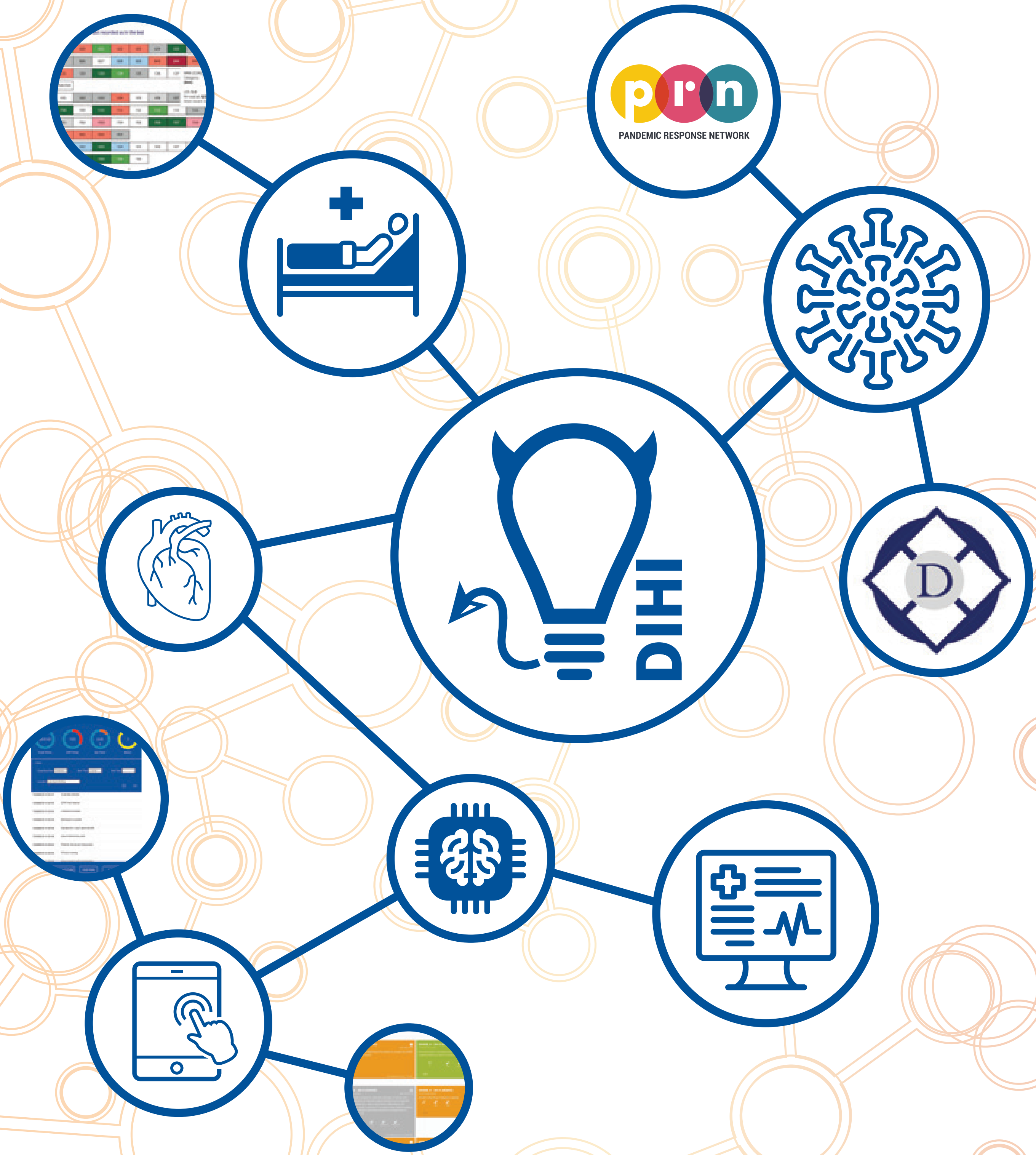
IMPACT REPORT
Issue 21

DIHI

Catalyzing transformative innovations in health and healthcare

Duke Institute for Health Innovation



Learn more about the cover by reading "Applying Machine Learning in the ED" (pg. 10), "Seeing & Responding to COVID-19" (pg. 24), and "HealthGuard: Machine Learning for Goals of Care Conversations" (pg. 42).

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2020 DIHI RFA Project Summaries

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About DIHI

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

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

Letter from the Directors

As 2020 draws to a close, we cannot help but reflect on the months past and how the ongoing pandemics of COVID-19 and racism have affected all aspects of life. Our people – faculty, staff and students – have met this moment with courage, tenacity, resilience and nothing short of heroism. We are grateful to the many clinicians, frontline staff, administrators, educators, researchers and learners at Duke Health who, despite the trying circumstances, have forged ahead in our mission of advancing health together.

In supporting that mission, our innovation projects this year have focused on the following broad thematic areas: preventing healthcare-acquired infections and enhancing quality and safety; enhancing transitions of care; team-based and new care models; building resilience and wellbeing; and population health and analytics. Amongst the 74 proposals received, ten were selected for funding and implementation. This report describes progress on these projects and the impact they have had on patient care. Several of these innovations are being scaled, and some have generated new IP and hence revenue streams that will further support research and innovation at Duke.

We have continued to deepen our expertise in developing and integrating machine learning and AI models to improve care. Many of DIHI's data science implementations have been published in peer-reviewed journals, and our team members have been invited to speak at national conferences. We also had the opportunity to host a highly successful national Machine Learning for Healthcare 2020 Conference. This allowed us to further showcase the outstanding work in healthcare innovation here at Duke and the immense power of collaboration when data engineers, statisticians, AI experts, programmers, physicians, nurses and other care providers and administrators identify problems and design solutions together to improve health and healthcare.

DIHI was a key collaborator in developing the Pandemic Response Network (PRN) along with the Population Health Management Office, Infectious Diseases, Critical Care and Duke Heart. The PRN helps communities stay safe by providing a symptom monitoring platform for COVID-19 and connecting people to the right resources and support that communities across the nation need. Along those same lines, we also developed the Symptom Monitoring App in partnership with Duke OIT. This digital health tool is being widely used by faculty, staff and students across the university to help ensure a healthy campus community.

Looking ahead to a new year in innovation, we end with a quote from the great Dr. King, "Of all the forms of inequality, injustice in health is the most shocking and inhumane." At DIHI, we are committed to leaning upon the principles of health and racial equity and social justice in seeking, developing, implementing and scaling innovations for the greater good of not just all our patients but also all members of the communities we touch at Duke and beyond. We look forward to sharing progress on a new generation of innovation projects in our next impact report.

Sincerely,
Bill Fulkerson and Suresh Balu

William Fulkerson, MD
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

"The 30-day readmission rate was 12.2% in the telehealth cohort and 23.1% in the historic comparison cohort."

TELEHEALTH FOR SNF TRANSITIONS

Use of Telehealth Video Conferencing to Improve the Hospital to SNF Care Transition

Following inpatient hospitalization, many older patients require post-acute short-term rehabilitation with skilled nursing facilities (SNFs) in order to regain their functional independence. This transition from hospital to post-acute care marks a pivotal shift in patient care with high potential for errors, readmission to the hospital, and mortality.[1] Discharge to SNF is a strong predictor of 30-day re-hospitalization, which is associated with an increased mortality rate even after adjusting for age, comorbidities, and prior healthcare utilization.[1] In 2017, the SNF 30-Day Observed All-Cause Readmission Measure was 18.87%.[2] Prior studies indicated that 31% to 67% of 30-day readmissions remain preventable.[3,4] Poor communication of critical information during the transition from hospital to SNF is a commonly cited reason for preventable readmissions.[5] Following in the footsteps of the HOPE workgroup and SNF Collaborative, our intervention seeks to improve the hospital to SNF transition through multidisciplinary video conferencing.

TEAM

Aubrey Jolly Graham, MD; Krishna Vanam, MD; Rachel Hughes, MD; Elisabeth Kidd, PA; Heidi White, MD; Colette Allen, NP; Juliessa Pavon, MD; Heather Jacobson, SLP; Will Knechtle, MBA, MPH; Julia Bellantoni

PROJECT IN BRIEF

Improve the care transition between the hospital and skilled nursing facility through multidisciplinary and multi-institutional review of patients in telehealth conferences. These conversations identified opportunities for health system improvements and resource connections that would reduce patient harm and need for readmission.

SOLUTION

In July 2019, we launched a weekly post-discharge telehealth video conference to facilitate multidisciplinary review of patients hospitalized at Duke University Hospital (DUH) or Duke Regional Hospital (DRH) and recently discharged to one of Duke Health's partner SNFs. These conferences allow for a brief discussion of each patient, focusing on transitional care pillars such as medication reconciliation, disease optimization, follow-up plans, and advanced care planning.

Our multidisciplinary team consisted of a hospital medicine lead clinician, pharmacists from DUH and DRH, a geriatrics fellow, the HOPE APRN, and a case manager. Between July 1, 2019 and January 31, 2020, 26 telehealth video conferences were held with two to three pilot SNFs to discuss 273 transitions among 260 distinct patients. Of our population, 64% were hospitalized at DUH and 36% were hospitalized at DRH. Seventy-one percent of patients were on general medicine service lines.

OUTCOMES

We observed a reduction in unplanned, all-cause 30-day readmissions as compared to patients discharged to the pilot SNFs during the same timeframe of the prior year (July 1, 2018 to January 31, 2019). The 30-day readmission rate was 12.2% in the telehealth cohort and 23.1% in the historic comparison cohort. Other clinical metrics observed include a decrease in 30-day mortality (5.4% in telehealth cohort vs. 9.0% in historic cohort) and a slight increase in 30-day ED return rate (9.5% in telehealth cohort vs. 7.8% in historic cohort). In addition, we descriptively evaluated errors identified in the care transition during the video conferences. Forty-four percent of patients reviewed had at least one error intervened on, with 54% of errors involving communication, 43% involving medication, and 3% involving DME.

NEXT STEPS

Several initiatives have been launched within the Duke University Health System to improve transitions of care from hospital to SNF, including efforts to improve hospital discharge forms and to develop practice guidelines for discharging providers. In addition to continuing the established telehealth conferences with our current SNF partners, we propose expansion of the program to additional partner SNFs. We also envision further partnerships with the PHMO and the potential use of this telehealth program to support other health system initiatives, such as the three-day waiver program and bundled payment models.

ACADEMIC OUTPUT

Clark E, Jolly Graham A, Bellantoni J, Malone D, Knechtle W, White H, Pavon J. Uncovering Errors in Transitions from Hospital to Nursing Home: A Video Telehealth Transitions Conference. NC ACP Meeting 2020 QI Category Winner. February 24, 2020.

DIHI INNOVATION SCHOLAR PERSPECTIVE

Julia Bellantoni

My year at the Duke Institute for Health Innovation (DIHI) provided a unique experience—as a third-year medical student—to participate in ongoing innovation within our health system. I thoroughly enjoyed the opportunity to pursue my clinical interest in geriatric populations alongside my passion for novel healthcare delivery models and develop skills in data abstraction and analytics. I appreciated the opportunity to collaborate on additional projects such as the Pandemic Response Network as DIHI responded to the new demands on healthcare innovation amidst COVID-19. I'm certain my experiences at DIHI will leave a lasting impact on my career in medicine, and I'm grateful for the opportunity to work and learn alongside leaders in innovation at Duke.

References

1. Burke RE, Whitfield EA, Hittle D, et al. Hospital readmission from post-acute care facilities: risk factors, timing, and outcomes. *J Am Med Dir Assoc.* 2016;17(3):249-255.
2. Centers for Medicare and Medicaid Services. Skilled Nursing Facility 30-Day All-Cause Readmission Measure (SNFRM) NQF #2510: All-Cause Risk-Standardized Readmission Measure Technical Report Supplement—2019 Update. https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/Value-Based-Programs/SNF-VBP/Downloads/SNFRM-TechReportSupp-2019-.pdf. Published April 2019. Accessed February 2020.
3. Ouslander JG, Lamb G, Perloe M, et al. Potentially avoidable hospitalizations of nursing home residents: frequency, causes, and costs: [see editorial comments by Drs. Jean F. Wyman and William R. Hazzard, pp 760-761]. *J Am Geriatr Soc.* 2010;58(4):627-635.
4. Vasilevskis EE, Ouslander JG, Mixon AS, et al. Potentially avoidable readmissions of patients discharged to post-acute care: perspectives of hospital and skilled nursing facility staff. *J Am Geriatr Soc.* 2017;65(2):269-276.
5. Dusek B, Pearce N, Harripaul A, Lloyd M. Care transitions: a systematic review of best practices. *J Nurs Care Qual.* 2015;30(3):233-239.

PREDICTING PEDIATRIC DETERIORATION

Development of machine learning models for early prediction of clinical deterioration in pediatric inpatients

Approximately 50,000 children die each year in the United States, and more than half die in inpatient hospital settings. Hospitalized children can decompensate quickly and predicting which child might decompensate is often difficult. Several pediatric early warning systems (PEWS) have been developed and studied for early detection of deterioration, with wide-ranging performance. Most PEWS currently in use, including the Duke PEWS (D-PEWS), almost exclusively use a patient's dynamic features, such as vital signs and appearance, although some studies have found static features, such as medical history, to be powerful predictors of deterioration. Although scores incorporating both static and dynamic features have improved performance, the increased number of features to be assessed by bedside nurses can be time-consuming and resource intensive.

TEAM

Zohaib Shaikh; Daniel Witt, MIDS; Tong Shen, MS; Will Ratliff, MBA; Harvey Shi; Michael Gao; Marshall Nichols, MS; Mark Sendak, MD, MPP; Suresh Balu, MBA, MS; Karen Osborne, BSN, RN; Karan Kumar, MD, MS; Kimberly Jackson, MD; Andrew McCrary, MD, MS; Jennifer Li, MD, MHS

PROJECT IN BRIEF

Using a wide range of clinical data available from the EHR, we developed easily implementable machine learning models that exhibit improved performance in predicting hourly risk of clinical deterioration in pediatric inpatients within 24-48 hours compared to our current institutional standard of care, the D-PEWS.

SOLUTION

Literature review suggested that machine learning models could utilize an increased number of clinical features to predict clinical deterioration in real-time with greater accuracy than PEWS. Duke University's Department of Pediatrics and the Duke Institute for Health Innovation (DIHI) formed a transdisciplinary team to develop a machine learning model that utilizes an extensive number of both static and dynamic clinical features to accurately predict a pediatric inpatient's risk of deterioration.

We collected data from 17,630 inpatient encounters for 10,388 unique pediatric patients (defined as <18 years of age at hospital admission or <25 years of age and on a pediatric service) admitted at Duke Children's Hospital from October 2014 to August 2018. Encounters limited to only the labor and delivery and/or neonatal units were excluded. The deterioration outcome was defined as an unplanned transfer to the intensive care unit (ICU) or inpatient mortality. Planned admissions to the ICU from the emergency department or the operating room, as well as direct transfers from labor and delivery, were excluded. A total of 542 predictive features were built from patient age, sex, comorbidities, and prior inpatient encounters at the time of admission, as well as vitals, lab results, orders, and medication administrations during the encounter. Features with numerical values were processed by creating event flags; 24-hour rolling mean, minimum, and maximum values; and hourly differences in values.

Non-numerical elements were mapped into features according to representations of clinical severity. The models are designed to generate hourly predictions of the risk of an unplanned transfer to the ICU over the subsequent 24 hours and mortality over the subsequent 48 hours. Models were trained using light gradient boosting machine (LGBM), lasso-penalized logistic regression (LR), and random forest (RF) methods. Models were evaluated on the accuracy of hourly predictions using area under the receiver operating characteristic curve (AUROC) and area under the precision-recall curve (AUPRC) and compared to the current institutional standard of care, the D-PEWS.

OUTCOMES

The project successfully developed a machine learning-based solution, applying the refined outcome of ICU transfer/mortality above for pediatric patients at Duke. We found that, of the 17,630 encounters we evaluated, 6% experienced the deterioration outcome (1,022 encounters with unanticipated ICU transfer, 108 culminating in inpatient mortality, and 81 with both events). In most encounters, ICU transfer was observed to occur soon after admission, with 25% of encounters experiencing a transfer in the first 22 hours, 50% in the first 101 hours, and 75% in the first 536 hours (mean 510 ± 959 hours).

The LGBM model performed best in predicting the deterioration outcome, with an AUROC of 0.847 (95% CI, 0.840-0.854) and AUPRC of 0.082 (95% CI, 0.076-0.090), compared to the RF (AUROC: 0.814 [95% CI, 0.806-0.822]; AUPRC: 0.067 [95% CI, 0.061-0.075]) and the LR models (AUROC: 0.812 [95% CI, 0.804-0.822]; AUPRC: 0.071 [95% CI, 0.065-0.078]) and D-PEWS (AUROC: 0.690 [95% CI, 0.686-0.693]; AUPRC: 0.066 [95% CI, 0.063-0.069]). We evaluated the performance of this LGBM model on pediatric patients hospitalized in 2019, achieving an AUROC of 0.786 and AUPRC of 0.0457.

Using this model, we designed a dashboard solution in Tableau to display deterioration risk scores on pediatric patients at Duke University Hospital. The risk scores are refreshed every hour based on real-time data in Maestro Care, and additional key data (e.g., vital and lab values) update every 10 minutes and are displayed alongside the risk score on the dashboard. We have developed a clinical workflow in partnership with the clinicians and Pediatric Rapid Response Team (PRRT) nurses on our team, and we plan to pilot our best-performing model within pediatric inpatient units in late 2020 in order to support proactive patient assessment by rapid response teams while collecting prospective data.

NEXT STEPS

As we complete the evaluation of the workflow and dashboard, we will assess the impact on patient outcomes. We plan to expand the solution to assess risk of additional clinical phenotypes, which will improve the dashboard as an actionable decision support tool. We will also incorporate a seamless interactive option for sharing patient risk updates as they occur, including notifications pushed to care teams for critical risk patients, to support immediate interventions and change the outcome trajectory for deteriorating pediatric patients at Duke.

ACADEMIC OUTPUT:

Shaikh Z, Witt D, Shen T, Ratliff W, Shi H, Gao M, Nichols M, Sendak M, Balu S, Osborne K, Kumar K, Jackson K, McCrary A, Li J. *Development of Machine Learning Models for Early Prediction of Clinical Deterioration in Pediatric Inpatients*. Poster presented at: Machine Learning for Healthcare 2020. August 8, 2020; formerly Durham, NC (virtual).

DIHI PERSPECTIVE

Containerized Software, DevOps, and Lean AI Health

Marshall Nichols, MS

As a small, active innovation group, we at the Duke Institute for Health Innovation (DIHI) are constantly looking for ways to improve not only our own internal development process, but also the way our development process integrates with the overall delivery of healthcare innovation at Duke. This began a few years back with the adoption of software containerization to give us better control over our deployments and the environments in which they ran. That extended naturally to adopting DevOps principles to improve visibility, automation, and speed of iteration on those deployments. Most recently, we've been extending these improvements beyond application development/deployment and into model development, optimization, and delivery of AI Health.

Prior to containerization (Docker), we deployed applications on virtual machines. We would develop our software on our laptops, install our software on these virtual machines, and spend significant effort on the care and feeding of these tools. Any time the virtual machine was updated, changed, had security patches applied, or had firewall rules updated, some intervention would be required to ensure the tool stayed online. There was always a risk that any of these upgrades or improvements would interact poorly with the systems our tool was based on and would require an indeterminate amount of time and effort to update the tool to work on the improved system. This has a side effect of discouraging updates due to the dread of potential re-work. This is dangerous in a world where health data security is paramount.

Docker has largely abrogated those concerns. Our only major operations requirement now is that the system we're using be able to support Docker. We, the developers, can control the environment within our containers. We can minimize the size of our deployments, and ensure their functionality on our laptops using the exact same environment that will constitute our final application deployment.

Patching, upgrading, and security improvements to the virtual machine are all able to be performed agnostic to the application we have deployed. As an example, SepsisWatch has now been deployed this way for nearly two years. All issues we've had since launch have been external to the application code, the Docker container housing that code, and the underlying relationship between the virtual machines and our containerized deployment.

With our environments essentially controlled, we've moved on to improving the way we deploy, monitor, and iterate on our applications. This is a multi-faceted approach most easily summed up by the adoption of DevOps principles:

1. Make small improvements often.
2. Automate testing and deployment wherever possible.
3. Seek feedback often from the end user to ensure development alignment.
4. Make development and operationalization processes transparent to the entire team.
5. Share success and failures—learn together, as a team.

This is, I believe, the ideal environment for developing and operationalizing digital innovation at Duke.

We began making heavy use of continuous integration/continuous delivery (CICD) pipelines in our development and operationalization processes. Many of our current deployments are now managed entirely through CICD, runnable by any member of the DIHI team and visible to all for rapid feedback and iteration in the event that issues do occur.

This, along with containerization, has greatly improved the consistency of the products we deploy, the speed with which we are able to develop them, and our ability to support each other internally.

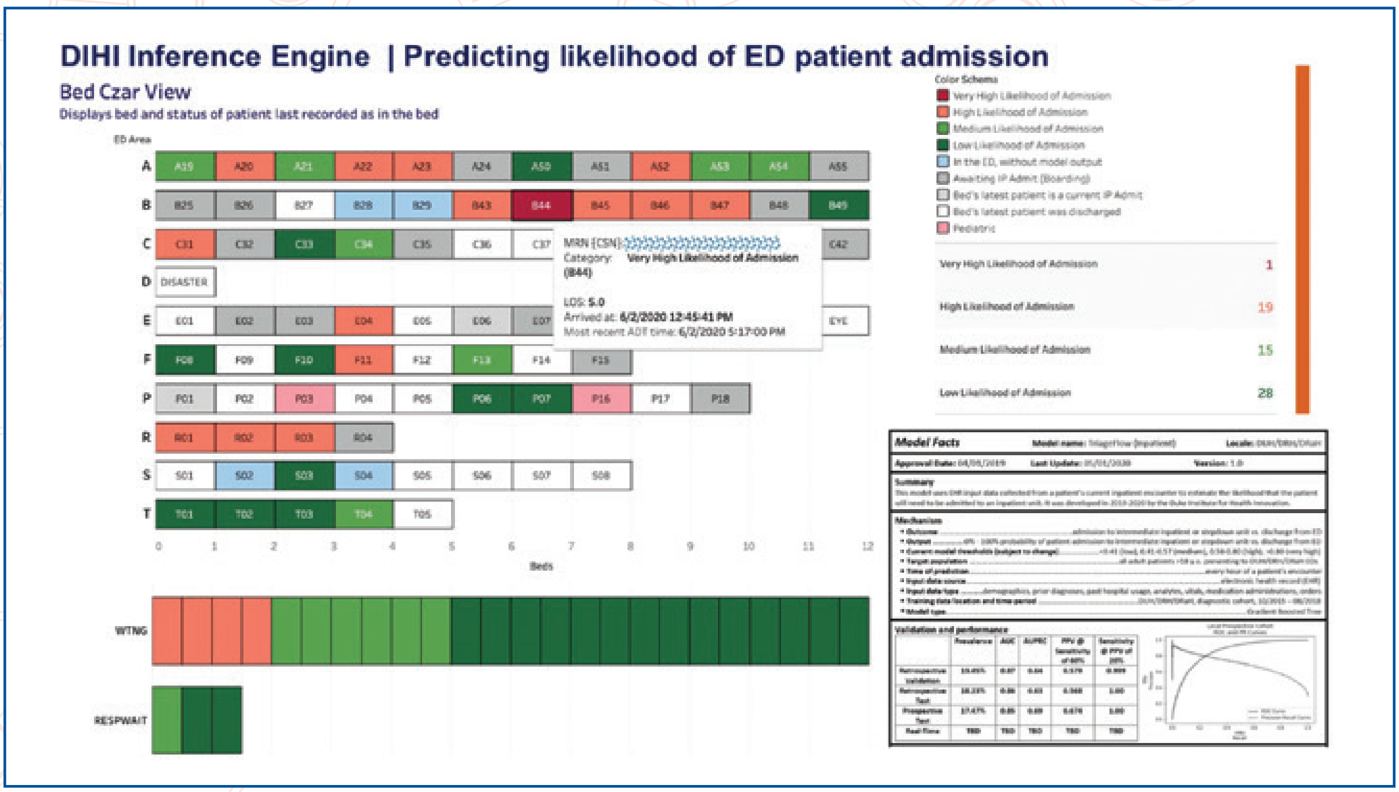
The adoption of these DevOps principles coincided serendipitously with the adoption of similar principles and software containerization at Duke Health Technology Solutions (DHTS). Significant effort at DHTS has been put toward operationalization of an on-premises Kubernetes (K8s) cluster, which we're beginning to adopt and are now piloting deployments into. Once complete, we'll move our entire development, deployment, and CI/CD process out of virtual machines and into Kubernetes full time.

This is, I believe, the ideal environment for developing and operationalizing digital innovation at Duke. With the help of DHTS and the Office of Academic Solutions and Information Systems (OASIS) teams, we already have four machine learning models deployed in the cluster along with a software scheduling and orchestration platform for coordinating their execution and monitoring. This is a HUGE step toward realizing an optimal, DevOps-guided, healthcare innovation pipeline at Duke.

In total, these improvements through containerization, DevOps, and Kubernetes adoption have taken our innovation development process output from one model developed and deployed per year to as many as 7 to 10 models developed and deployed per year, depending on their complexity. This is all while improving the transparency, stability, and time-to-impact of every innovation deployed.

Our next steps are to move our machine learning model training, development, and evaluation processes entirely into the same containerized, DevOps guided, CI/CD, and Kubernetes deployed pipelines. With the help of new DHTS-supported tools like Hashicorp Vault, Timescale DB, PostgresSQL, Apache Airflow, and their ongoing support of Kubernetes, we will further lower the barrier between model/application development at DIHI and deployment into production by DHTS. This is the way.

Figure 1. Applying machine learning in the ED with a real-time visual dashboard. The 2020 DIHI RFA Project Summary is on Page 10-11.



APPLYING MACHINE LEARNING IN THE ED

Using machine learning in emergency department flow

Timely triaging and accurate disposition of patients in an emergency department is difficult, but it enables improvement of clinical outcomes and improved flow of patients across the health system. We embarked on a project that aimed to develop and validate a machine learning model that could reliably predict the need for inpatient and intensive care unit (ICU) admission for patients who present to the Duke University Hospital (DUH) Emergency Department (ED). The integration of this model into the clinical workflows would therefore help augment patient flow from ED arrival to inpatient bed assignment.

TEAM

B. Jason Theiling, MD; Mark Sendak, MD, MPP; Michael Gao; Neel Kapadia, MD; Cara O'Brien, MD; Dan Buckland, MD; Alex Fenn; Connor Davis; Will Ratliff, MBA; Will Knechtle, MBA, MPH

PROJECT IN BRIEF

This pilot project aimed to develop and validate a machine learning model that could reliably predict the need for inpatient and intensive care unit admission for patients who present to the DUH Emergency Department. The ultimate implementation of this model into the clinical setting would therefore help augment patient flow from ED arrival to inpatient bed assignment.

SOLUTION

The primary aim of this project and associated follow-on study was to develop and validate two machine learning models that utilize both historic and current-visit patient data from the electronic health record (EHR) to predict the probability of patient admission to either an inpatient unit or ICU. These models run every 15 minutes from a patient's initial presentation to the ED (i.e., triage) throughout a patient's stay in the ED until a disposition decision is made. Another goal of this effort was to provide a framework for clinical integration of the models so that they improve patient flow throughout the hospital system.

Real-time visual dashboards were developed to display the models' current prediction scores in a color coded graphical interface that was both robust in its content and quickly made actionable (Figure 1. Page 9.) These dashboards are available to individual providers working clinically during a shift, but more importantly to the DUH patient placement team and the ED patient flow coordinator. By providing early and accurate information about the likely need for an inpatient admission, patients can be more easily prioritized for movement to an acute care bed within the ED.

Additionally, by utilizing both the summary view, which includes total number of likely inpatient and ICU admissions, as well as patient-level data, DUH Patient Placement can more efficiently identify and assign an inpatient bed for ED patients as well as inform decisions made around movement of other patient populations within the hospital (e.g., outside hospital transfers).

OUTCOMES

Our study also goes beyond the validation metrics of other previously published models and demonstrates continued high levels of predictive accuracy for a time period outside of the model training time period. This was achieved both in the 2019 cohort, as well as in the 2020 real-time data collected via the models' integration into the Duke University Health System (DUHS) EHR. These validations on more recent patient cohorts have implications for the generalizability of the model to be used in a real-time setting to help support clinical decision making.

NEXT STEPS

This model has been trained using DUHS data and will be rolled out to Duke Raleigh Hospital and Duke Regional Hospital emergency departments and patient flow departments. Additionally, the team is developing plans to integrate the current models into the GE Health Care Hub and various tiles used for patient flow.

Work from this DIHI RFA project led to a follow-on $50,000 award from Duke/Duke-NUS Medical School for a collaboration with SingHealth, Singapore's largest cluster of healthcare institutions, to validate their admissions model on our data and our models on their ED data.

ACADEMIC OUTPUT

Fenn A, Davis C, Kapadia N, Buckland D, Nichols M, Gao M, Knechtle W, Balu S, Sendak M, Theiling BJ. *Using Machine Learning in Emergency Department Patient Flow.* 2019 Duke AI Health Data Science Showcase. November 25, 2019; Durham, NC.

Fenn A. (2020, February 22). *Development of Machine Learning Models to Predict Admission from ED to Inpatient and Intensive Units* [Poster Presentation]. 2020 Society of Academic Emergency Medicine (SAEM) Southeastern Regional Conference, Greenville, SC. https://ghscme.ethosce.com/courses/2020SAEM https://www.youtube.com/watch?v=tQl-mENo3BbA. Best Student Poster February 2020.

Fenn, A. (2020, May 12). *Development of Machine Learning Models to Predict Admission from ED to Inpatient and Intensive Units* [Oral Abstract]. 2020 Society of Academic Emergency Medicine (SAEM) National Conference, Denver, CO [Cancelled due to COVID-19]. https://www.youtube.com/watch?v=tQl-mENo3BbA&list=PLs5gzUFrD1rvhEWW7M9KrL5f-6DGBNarEv&index=24

DIHI INNOVATION SCHOLAR PERSPECTIVE

Alex Fenn

At the Duke Institute for Health Innovation (DIHI), I had the opportunity to help develop a machine learning model that predicts the likelihood that a patient in the emergency room will be admitted to or discharged from the hospital. When thinking about my experience at DIHI, I find it helpful to break my year down into both hard and soft skills.

With regard to hard skills, my project required that I learn a programming language (Python). As I had no formal coding background, this was undoubtedly a large task with a steep learning curve—but the mentorship and teaching I received at DIHI helped make this endeavor feasible. Throughout the year, my programming skills improved to the point where I had multiple, non-DIHI peers reach out to me to ask for assistance with data analysis and manipulation, allowing me to collaborate on multiple other projects. Via the DIHI scholar curriculum—the journal clubs and fireside chats, to name a few—I was able to more fully understand the intricacies of how the health system operates, something that is lacking in a traditional medical school curriculum.

However, when I think about my time at DIHI, what has made the greatest impact is the way in which I think about healthcare-related problems and the process by which one creates transformational change. I strongly believe that due to the environment DIHI has created—a collaborative, all-hands-on-deck, constantly questioning and refining sphere—anyone who spends time at DIHI is much better equipped to tackle the ever-nuanced art of improving healthcare quality and delivery. My experience over the last year was invaluable, and I know that I will continue to use what I learned at DIHI throughout my career.

ENHANCING PATIENT-PROVIDER INTERACTIONS WITH NLP

Reducing Provider Burden While Improving Patient Experience by Applying Natural Language Processing to Build an Intelligent Response Engine

In 2019, over 140,000 patients sent Duke Health 750,000 messages specifically requesting medical advice, and an additional 90,000 messages were received related to medication renewal or refill. Currently, Duke clinicians are fielding hundreds of thousands of patient messages manually, without the help of available machine learning techniques to triage messages.

In the cardiology service line, Duke Health identified several message categories that could either be automated or directed to front-desk administrators, rather than to MD/APP clinicians. Over 13% of the 750,000 medical advice requests were related to administrative tasks, 12.2% were related to scheduling questions, and 10.5% were free-text requests for simple prescription refills.

SOLUTION

We built an "Intelligence Response Engine" that took the unstructured free text received through patient portal messages and applied natural language processing (NLP) to appropriately triage messages and direct users.

TEAM

Jedrek Wosik, MD; Shijing Si, PhD; Will Ratliff, MBA; Ricardo Henao, PhD; Manesh Patel, MD; Larry Carin, PhD

PROJECT IN BRIEF

Patient portal messaging is increasingly popular for patient-provider communication but can increase clinician workload. Natural Language Processing (NLP) can identify messages by topics (e.g., most frequently asked questions) and classify messages for triage purposes (clinical vs. non-clinical, emergency vs. non-emergent, etc.).

Triaging these messages will greatly reduce clinician time spent in MyChart and potentially reduce costly burnout. Building this classification system enabled us to identify emergent messages not appropriate for asynchronous patient portal messages, which are designed to allow 24 to 72 hours for replies. A web app was developed to use the "Intelligent Response Engine" to warn users if their message appeared have an emergent nature (e.g., suggestion of acute heart attack, stroke, or clinical symptoms warranting a nurse hotline or 911 call); see Figure 1.

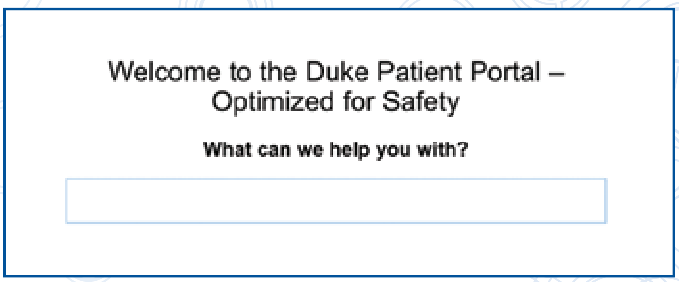
OUTCOMES

With a custom-built Epic application programming interface (API), we are now able to identify MyChart message topics (e.g., most frequently asked questions). We can apply our solution to both patient portal messages as well as telephone encounters, which both have a significant proportion of interactions that could be converted to a patient self-service tool or an administrative, non-clinical group (see Table 1).

NEXT STEPS

Currently, we are identifying trends in the patient portal topics related to flu as well as to COVID-19, particularly for patients who tested positive in the Duke University Health System. This identification could be used to provide early signals of local flu and COVID-19 outbreaks before increases in health system lab testing or increases in health authority-reported cases are known. Our work has led to a deep understanding of patient portal communications and how Duke could apply NLP to improve patient care, engagement, and clinician and staff efficiency and resiliency.

Figure 1.



Grants: NIH Loan Repayment Program (LRP) grant in August 2020: "The impact of nuisance bleeding on medication adherence and patient outcomes: A real-world analysis of electronic health record data using natural language processing (NLP)"

Demo: Duke Patient Portal Optimized for Safety (web app that identifies emergent clinical messages)

ACADEMIC OUTPUT

Si, S.; Wang, R., Dov, D., Wosik, J., Henao, R., Carin, L. *Students Need More Attention: BERT-based Attention Model for Small Data with Application to Automatic Patient Message Triage*. Poster presented at: Machine Learning for Healthcare 2020. August 8, 2020; formerly Durham, NC (virtual).

Wosik, J., Si, S., Henao, R., Sendak, M., Ratliff, W., Balu, S., Poon, E., Carin, L., Patel, M. *Topic Modeling of Patient Portal and Telephone Encounter Messages: Insights from a Cardiology Practice*. Poster presented at: Machine Learning for Healthcare 2020. August 8, 2020; formerly Durham, NC (virtual).

Wosik, J., Shijing, S., Henao, R., Carin, L., & Patel, M. R. (2019). Artificial Intelligence to Identify Commonly Asked Questions via an Electronic Patient Portal: Lessons from a Cardiology Department within a Large Health System. *Journal of the American Heart Association, 140* (Suppl_1).

Table 1.

PATIENT PORTAL MESSAGE TOPICS: TOTAL MESSAGES= 167,030				
Administrative 22,125 (13.24%)	Scheduling 20,327 (12.17%)	Complex prescriptions 19,659 (11.77%)	Simple prescription 17,495 (10.47%)	Afib/Afl 16,483 (9.86%)
Medications +symptoms 15,539 (9.30%)	Clinical symptoms 15,061 (9.02%)	Vitals 14,986 (8.97%)	Results (labs/ procedures) 14,605 (8.74%)	Miscellaneous (social) 10,755 (6.43%)
TELEPHONE MESSAGE TOPICS: TOTAL MESSAGES= 822,597				
Scheduling, clinical follow-up 194,408 (23.63%)	Clinical questions, scheduling, appointments 147,731 (17.96%)	Lab results, interpretation/ recommendations 82,441 (10.02%)	CT surgery discharge follow-up, other questions 69,243 (8.42%)	Organ donation/ Transplant Candidacy 69,130 (8.40%)
Questions about symptoms 66,876 (8.13%)	Discharge follow-up questions 65,446 (7.96%)	Holter reports, Cardionet Summary 53,915 (6.55%)	LVAD INR Note 50,425 (6.13%)	Discharge follow-up questions 22,982 (2.79%)

DIHI PERSPECTIVE

SymMon: Duke Symptom Monitoring

Mike Revoir and Matt Gardner

As Duke students, faculty, and staff looked forward to reengaging in campus activities for the fall 2020 semester, the need arose for a technology solution focused on early detection of COVID-19 symptoms and tracking potential cases. In response to this need, Duke University used the secure REDCap platform to build a daily symptom reporting Web portal. This REDCap based system served the initial need, but there was consensus to extend the solution with a mobile app that was simple to use and facilitated daily symptom reporting compliance.

The initial capabilities envisioned for the mobile app were as follows:

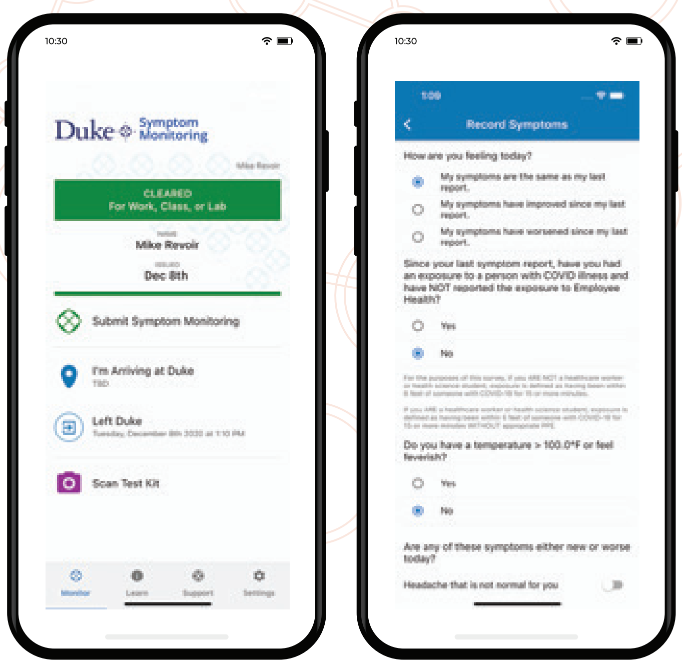
- Integration with Duke single sign-on and multi-factor identity verification, to ensure that all data was captured in the context of a valid Duke identity.
- Capture of daily self-reported coronavirus related symptoms.
- Daily reminders to self-report symptoms, to encourage and facilitate reporting compliance.
- Capture of self-reported campus arrival and departure, to assist in tracking the location of individuals who report symptoms of concern.
- Capture (scan) of barcode on a self-administered test kit, to support downstream tracking of test results and disposition of test kits.

SOLUTION

The Duke Institute for Health Innovation (DIHI) partnered with the Duke Office of Information Technology (OIT) to build the mobile app platform, named SymMon, with the goal of it being available in app stores when students returned to campus—less than four weeks from project initiation.

The DIHI/OIT partnership turned out to be very effective. Duke OIT expedited provisioning of required infrastructure such as identity management services, application servers, and database servers, while DIHI focused on building the application components. The mobile app (Figure 1), which runs on both iOS and Android devices, communicates with a Web services API that captures all self-reported data and stores it in a secure database hosted by the OIT team.

Figure 1.



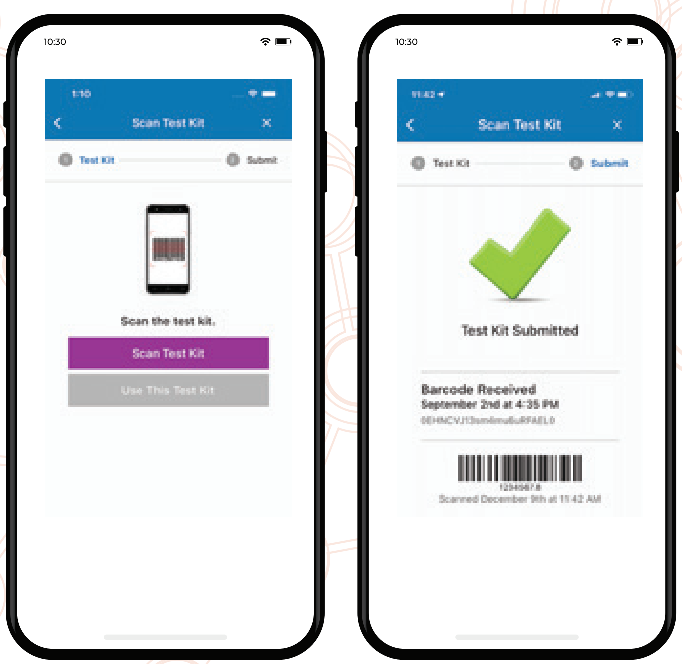
The OIT team integrates this data back into the broader REDCap system to support coronavirus tracking workflow for Student Health and Employee Occupational Health & Wellness (EOHW). After four weeks of development sprints, the app was deployed for limited use by returning student athletes, and a few weeks later to the broader Duke community. The user population quickly ramped up to over 11,000 daily users on weekdays, with very few reported issues.

The app was also extended to support periodic surveillance testing. Students and staff use the app to scan the barcode on a self-administered test kit (Figure 2). This scan action links the test kit to their DukeCard ID and allows the Duke Human Vaccine Institute (DHVI) to track the sample test results and disposition.

IMPACT

Charles L. Kneifel, PhD, senior technical director at OIT, said, "The impact of the SymMon app and DIHI's contribution to the app cannot be overstated. The app has been a significant contributor to the successful reopening of Duke for both research needs and to the students living on campus and in the surrounding area. The inclusion of the barcode feature has been instrumental in making it possible for Duke to test well north of 12,000 students, faculty, and staff on a weekly basis."

Figure 2.



"The impact of the SymMon app and DIHI's contribution to the app cannot be overstated. The app has been a significant contributor to the successful reopening of Duke for both research needs and to the students living on campus and in the surrounding area."

ACADEMIC OUTPUT

Denny, T. N., Andrews, L., Bonsignori, M., Cavanaugh, K., Datto, M. B., Deckard, A., DeMarco, C. T., DeNaeyer, N., Epling, C. A., Gurley, T., Haase, S. B., Hallberg, C., Harer, J., Kneifel, C. L., Lee, M. J., Louzao, R., Moody, M. A., Moore, Z., Polage, C. R., ... Wolfe, C. R. (2020). Implementation of a Pooled Surveillance Testing Program for Asymptomatic SARS-CoV-2 Infections on a College Campus — Duke University, Durham, North Carolina, August 2–October 11, 2020. MMWR. Morbidity and Mortality Weekly Report, 69(46). 1743-1747. https://doi.org/10.15585/mmwr.mm6946e1

CHEST PAIN DECISION SUPPORT IN THE ED

Real-Time High-Sensitivity Cardiac Troponin Decision Aid

Chest pain is one of the most common complaints of patients presenting to the emergency department (ED) (Figure 1). Our primary goals were to improve the accuracy of the diagnosis of chest pain, improve ED throughput, and reduce clinician burden. Two independent algorithms, the new fifth generation high-sensitivity troponin (hsTn) and the HEART Score, contain numerous decision nodes, demanding a substantial effort on the part of the clinician just to understand how each of the algorithms work.

The typical decision aid for the ED clinician has been (separate) printed pocket cards that do not provide the details needed to implement the algorithms to maximal effectiveness. Our goal was to simplify use of these algorithms and advance care by providing best practice guidance for disposition of ED patients with chest pain.

TEAM
James Tcheng, MD; Kristin Newby, MD, MHS; Jedrek Wosik, MD; Charles Gerardo, MD; Clay Musser, MD; Tres Brown; Jeremy Poling; Bruce Lobaugh, PhD; Mike Revoir; Will Knechtle, MBA, MPH

PROJECT IN BRIEF
Developed a web-based app that computerizes two algorithms into one CDS tool, an hsTn algorithm and HEART algorithm, and then presents summative clinical care and disposition recommendations based on the combined results. While the app can be accessed via a standard browser URL, we placed multiple links within Maestro Care to launch the app directly from within a patient's chart and optimize clinician convenience (Figure 2 and Figure 3).

SOLUTION

The Chest Pain Assessment Tool (CPAT) is a clinical decision support (CDS) tool to assist in evaluating the patient presenting to the ED with chest pain or other potential signs and symptoms of cardiac ischemia. CPAT combines two separate standard of care algorithms: interpretation of the hsTn and the HEART Score for risk stratification of the patient with chest pain. CPAT computerizes the complex hsTn algorithm and the HEART Score to develop best-practice disposition recommendations.

Figure 1.

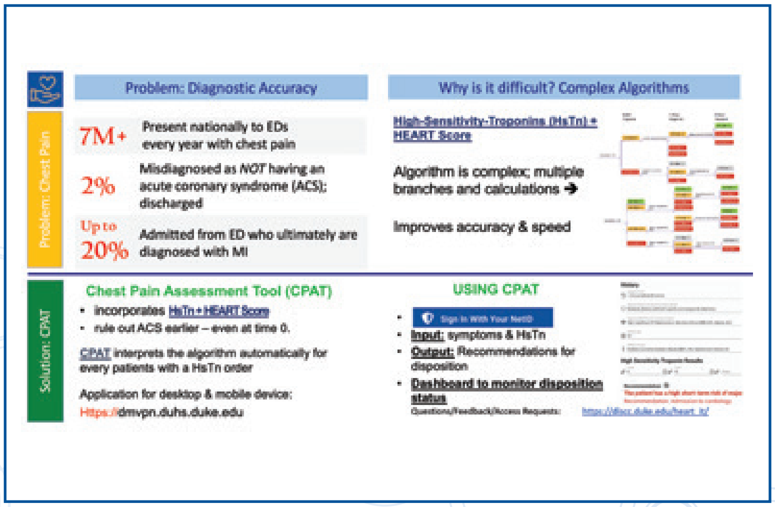


Figure 2.

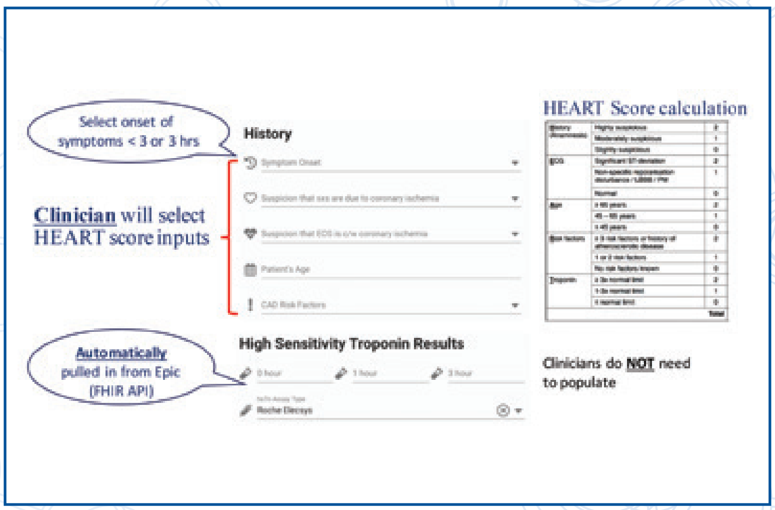


Figure 3.

The implementation reduces clinician burden by automatically extracting demographic and laboratory data from Maestro Care via Fast Healthcare Interoperability Resources (FHIR) standards. Finally, it is an application designed for the future.

It is modular in design, in order to permit multiple types of deployment, and it was built to accommodate all hsTn assays in use (of which there are currently five, each with different reference ranges) as well as new ones that are being developed.

OUTCOMES

We successfully built the FHIR-enabled web app per the specifications of a clinical group led by Drs. Kristin Newby and James Tcheng. The app was released in beta in 2019 and iteratively improved upon beta status. The production version of this app was deployed at the Duke University Hospital ED in July 2020. The acceptance of the app has been universally positive by ED attending physicians and house staff. With a recently approved IRB, we are commencing a study to track clinical and operational impacts of the app.

NEXT STEPS

The design and programming of CPAT adhered to best practice standards for multi-platform implementation and deployment. Two additional versions are planned: a simpler standalone web app without data integration but with local data storage, and a mobile app. The next phase will be to deploy to the other Duke hospitals, potentially followed by Duke affiliates and Duke LifePoint partners.

ACADEMIC OUTPUT

Wosik, J., Revoir, M., Doshi, P., Knechtle, W., Balu, S., Sendak, M., Ratliff, W., & Tcheng, J. (2020, November 17). *Chest Pain Assessment Tool (CPAT): A Real-time Clinical Decision Support Aid for Evaluation of the ED Patient with Chest Pain*. AMIA 2020 Virtual Annual Symposium: HL7 FHIR Applications Competition.

REMOTE MONITORING FOR ONCO-PRIMARY CARE

Transforming Cancer Care: Bringing PCPs "Back" Into Cancer Care Through Onco-Primary Care

Despite advances in cancer therapy and treatment, many cancer patients are more likely to die from cardiovascular disease, heart attack, or stroke than from their primary cancer. Why? Because providers and patients do not pay enough attention to common comorbidities during or soon after cancer therapy.

SOLUTION

We have developed an automated approach for home blood pressure (BP) management using device-enabled patient reported outcomes. Home blood pressure measurements taken on a QardioArm Bluetooth BP cuff are collected by the patient's iPhone and shared with the Epic MyChart app using Apple HealthKit. These values are then imported from the MyChart app to a Maestro Care flowsheet. Each Monday, our newly developed algorithms evaluate the measurements from the prior week and score the patient on their BP control (with a goal of <140/30) as well as BP process (with a goal of 3-4 measures each week, with at least two morning measurements and one evening measurement).

TEAM

Kevin Oeffinger, MD; Leah Zullig, PhD; Mo Shahsahebi, MD, MBA; Renee Avecilla, MD, CCRP; Coleman Mill, MA, CCRP; Will Ratliff, MBA; Danielle Brander, MD; Michael Harrison, MD; Susan Dent, MD; Michel Khouri, MD; Kevin Shah, MD; Anthony Viera, MD; Karen Goldstein, MD; Terry Hyslop, PhD

PROJECT IN BRIEF

Developed, implemented, and evaluated an automated, asynchronous home blood pressure management workflow to improve blood pressure control for and PCPs' engagement with patients on active chemotherapy.

Based on these scores, the patient is sent a MyChart message offering encouragement to keep up the good work, offering feedback to correct their BP process or notifying them that their primary care provider (PCP) has been alerted that they are above their BP goal. PCPs are informed of the workflow upon patient enrollment and are instructed on how to access this HealthKit flowsheet in Maestro Care. Each week in which a PCP's patient is above his/her goal BP, the PCP receives a notification in Maestro Care recommending blood pressure management.

OUTCOMES

We developed, tested, and implemented a workflow to connect data from the QardioArm cuff to a Maestro Care flowsheet. We also designed, built, tested, and implemented a "semi-automated" package of Maestro Care tools to act upon home BP data in a bulk manner. A fully automated process is in development. Our study was interrupted when enrollment was temporarily halted due to the COVID-19 pandemic. At that time, we had enrolled four chronic lymphocytic leukemia (CLL) patients, all of whom have now completed the study.

We created provider-facing Maestro Care tip sheets for connecting Duke MyChart to iPhone HealthKit and accessing HealthKit data in Maestro Care. Since the pandemic has limited face-to-face configuration of an enrollee's iPhone, we developed and are testing an iPhone configuration self-set-up workflow and tip sheet that we hope will allow us to enroll patients virtually once enrollment reopens.

NEXT STEPS

The workflows developed here can have a wide range of applications across numerous patient populations. Researchers in the Duke Adult Blood and Marrow Transplant Program are using similar workflows to examine remote management of blood sugars in diabetics. Currently, data transfer to the Duke MyChart app is only possible via Apple HealthKit, but Android users will soon be able to use these workflows once Duke Health Technology Solutions (DHTS) opens that link. Once our workflow is fully automated, it can serve as a use case for low-touch, remote chronic disease management across large populations.

ACADEMIC OUTPUT

Building off of the work done for this Duke Institute for Health Innovation project, the team was awarded a $3.7 million grant for a 5-year study aimed at optimizing management of HTN, diabetes, and lipid disorders among patients with newly diagnosed solid tumors (ONE TEAM Study, R01CA249568; MPI: Oeffinger and Zullig).

DIHI INNOVATION SCHOLAR PERSPECTIVE

Stephanie Skove

As a third-year research scholar with the Duke Institute for Health Innovation (DIHI), I had the opportunity to work with an interdisciplinary team of physicians, nurses, and data scientists to design and implement a machine learning early warning score to predict adult inpatient deterioration. The goal of the project was to identify patients at a high risk of clinical deterioration and to assist the rapid response team with proactive monitoring of these patients. I was able to take a lead role on this project with not only the development and creation of the model, but also in discussions of how the model would be utilized as a clinical decision support tool.

Prior to my experience as a DIHI scholar, I had little experience in the world of machine learning and artificial intelligence. Through the amazing team at DIHI, I was able to dive into a growing area of research that will surely continue to have a significant impact in the field of medicine. This experience helped me realize that pushing boundaries in medicine doesn't always mean discovering the next cure—it can also mean evaluating our healthcare system from a different angle by asking why we do things and how we can do them better. I am excited to continue to bring this type of multidisciplinary problem solving to the forefront of patient care and medical education.

PREVENTING CTICU BOUNCEBACKS

Machine-Learning Algorithm to Predict Unplanned ICU Readmissions in the Cardiothoracic Surgical Population

Duke University Health System's (DUHS's) failure to rescue (FTR) after surgery—the inability to prevent death after the development of a postoperative complication—is higher than the national average (PSI 04 indicator across all surgical services is 19.2% vs. 16.2% nationally). Promoting early identification of clinical deterioration and timely treatment of postoperative complications is a critical component of quality improvement, as delayed escalation of care due to delayed identification of patient deterioration is a key contributor to increased FTR rates. Furthermore, patients readmitted to the intensive care unit (ICU) demonstrate increased mortality, length of stay, and healthcare expenditures compared to those not readmitted. Issues tend to be amplified during transitions of care, typically between a highly monitored environment (e.g., the ICU) to a less monitored one, e.g., a step-down unit or SDU.

Improving monitoring by using low-specificity alerts dependent on very basic algorithms has resulted in alarm fatigue. Performance characteristics and adoption of "off-the-shelf" aggregate early warning scores (e.g., NEWS) in the Duke ICU population were poor. Most current rule-based ICU decompensation models (i.e. APACHE, SAPS, NEWS, MEWS, etc.) are limited in terms of static prediction for general mixed medical-surgical ICU patients.

TEAM

Mihai Podgoreanu, MD; George Cortina, MD; Shujin Zhong; Mark Sendak, MD, MPP; Michael Gao; Will Ratliff, MBA; Marshall Nichols; Jill Engel, DNP; Kelly Kester, MSN; Mary Lindsay, MSN; Ashok Bhatta, MSc; Ricardo Henao, PhD; Jacob Schroder, MD; Will Knechtle, MBA, MPH; Suresh Balu, MBA

PROJECT IN BRIEF

1. Map the flow of Duke adult cardiothoracic (CT) surgical patients across the continuum of care
2. Develop machine learning models for predicting clinical deterioration in CT surgical patients, with two distinct event horizons: (1) at the time of CTICU discharge/transfer to SDU: predict the likelihood of CTICU readmission or death within the next 14 days, and (2) In the CT-SDU: continually predict the likelihood of CTICU readmission or death within the next 48 hours.

Furthermore, no predictive algorithms for clinical deterioration currently exist for adult cardiothoracic surgical patients. Targeting this population may influence both the performance of predictive models and the effectiveness of interventions to reduce FTR.

SOLUTION

A multidisciplinary team of clinicians from Duke Cardiothoracic Anesthesiology and Critical Care, Duke Cardiothoracic Surgery, Duke Heart nursing and advanced practice providers (APP) leadership, and data scientists from the Duke Institute for Health Innovation focused on enhancing transition of care between the cardiothoracic ICU (CTICU) and cardiothoracic step-down unit (CT SDU). They sought to develop and validate predictive models to rapidly and accurately identify adult cardiothoracic surgical patients at high-risk for postoperative clinical deterioration necessitating unplanned readmission to the CTICU from the CT SDU.

Our first objective was to develop a framework for concurrent multi-patient, multi-diagnosis, and multi-stream temporal analysis of CTICU and CT SDU physiological data (vital signs, medical devices, laboratory) in real time for clinical management and historically for clinical research.

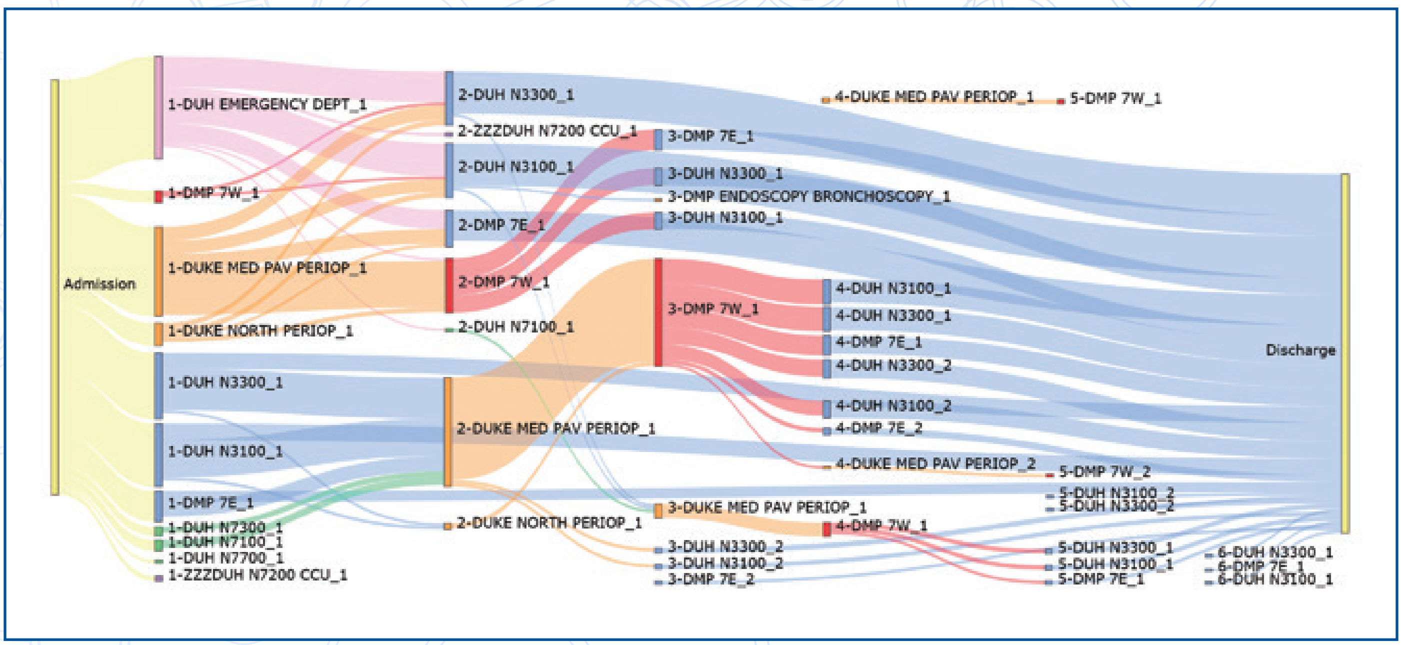
We mapped CT surgical patient flow and integrated this with physiologic data to develop dynamic machine-learning predictive models.

OUTCOMES

Cardiothoracic surgical patient flow during an index hospitalization was mapped to visually display and assess the CTICU readmission phenotype (Figure 1). Among our cohort of encounters, 564 (10%) conformed to the phenotype.

Our team developed two distinct clinical deterioration models. The model development cohort consisted of 5,559 adult patients who underwent cardiothoracic surgery between August 2015 and October 2018, followed by CTICU care and transfer to a CT SDU.

Figure 1. Sankey diagram to visualize flow of patients readmitted to the CTICU during index hospitalization. Predicting the CTICU readmission phenotype through identification of patients at risk – both at the time of CTICU discharge (Model I) and by increased surveillance in step-down units (Model II) could reduce length of stay, complications, and failure to rescue rates.



Model I: Predicting clinical deterioration at the time of CTICU discharge. Multiple domain input features were used. (Table 1). Outcome: composite of CTICU readmission from CT SDU or death within a 14-day window from CTICU discharge (Table 2).

Model II: Predicting clinical deterioration while in the CT SDU. Outcome: composite of CTICU readmission from CT SDU or death within 48 hours (Table 2).

We ensured the model had a scalable framework to stratify patient risk prospectively and sequentially during hospital admission. This was especially important for deteriorating ward patients, for whom other early warning scores omit the interactions of chronic health status, presenting condition, and post-admission course. Current performance metrics suggest that our models identify physiologically relevant factors in their prediction and outperform rule-based approaches.

Accurate prediction of unplanned readmission could be used in decision support tools to inform ICU discharge readiness and target resources for SDU care (including increased patient surveillance), especially for high-risk patients requiring complex discharge planning.

NEXT STEPS

The team's next steps involve:

1. Further model refinement, including additional model architecture that considers temporal aspects of the data without needing feature engineering across set intervals (i.e., sliding time windows);
2. Running the model silently for prospective validation; and
3. Investigating means to evaluate model performance beyond AUROC in a way that reflects its implementation and use in the hospital.

Table 1. Multiple domain input features for ML model of patient decompensation (CTICU readmission or mortality)

FEATURES (NUMBER OF DATA ELEMENTS)	VARIABLES
I. PATIENT-SPECIFIC DISEASE PROCESSES, GROUPED TRENDS	
Demographics (2)	Age, Gender
Encounter Info (10)	(12 and 3 month) Count of General Admissions, ED Visits and CTICU Admissions; Length of Stay in CTICU and/or Hospital Admission
Comorbidities (282)	Clinical Classification Software of ICD-10 Codes*
Laboratory Values† (25)	Albumin, ALT, Ammonia, Anion Gap, Arterial Bicarbonate, Arterial PCO_2, Arterial pH, AST, Bands, BUN, Creatinine, CRP, ESR, Fibrinogen, Glucose, Hematocrit, Hemoglobin A1c, INR, Lactate, LDH, Magnesium, OR Arterial PO_2, Platelets, Potassium, Sodium, Venous PCO_2
Physiologic Measures† (11)	Blood Pressure, BMI, Cardiac Index, Cardiac Output, Height, Level of Consciousness, Pulse, Pulse Oximetry, Respiratory Rate, Urine Output, Weight
Patient status‡ (4)	Delirium, Dyspnea, Hypothermia, Length of Stay, Stroke Work-up
II. CLINICAL INTERVENTIONS (MEDICATION PROFILES, TREATMENTS, ACTIONS AND ORDERS), GROUPED TRENDS	
End Organ Support‡ (9)	Bilevel Positive Airway Pressure, Continuous Positive Airway Pressure, Continuous Renal Replacement Therapy, Extracorporeal Membrane Oxygenation, Impella, Intra-aortic Balloon Pump, Mechanical Ventilation, Ventricular Assist Device (VAD) (durable), VAD (temporary)
Orders for labs‡ (8)	Arterial Blood Gas, Blood Typing, Coagulation Panel, Cytomegalovirus, Human Papilloma Virus, JC virus, PT, INR, Toxoplasmosis, Sputum Culture
Orders of procedures/ status changes‡ (12)	Arterial Line Insertion, Arterial line Removal, Chest Tube Placement, Intubation, NPO, Peripherally Inserted Central Catheter (PICC) insertion, PICC Removal, Stroke Workup, Tracheostomy Placement, Transfusion (Fresh frozen plasma/Platelet/RBC/Cryoprecipitate), VAD Placement, Wound Care
Orders for imaging/monitoring‡ (6)	Chest Radiograph, ECG, Echocardiogram, Kidneys Urine Bladder Radiograph, Telemetry, Ultrasound (any)

*-Classification categories listed at: https://www.hcup-us.ahrq.gov/toolssoftware/ccs10/CCSCategoryNames(FullLabels).pdf
†-numeric data summarized over encounter using: max, min, mean, standard deviation, 1st quartile, 3rd quartile number of entries, time of first order, time of last order
‡-boolean event data summarized over encounter using: any event occurred, number of events, time of first event, time of last event

To enable continuous predictive analytics monitoring at scale, DUHS leadership, in partnership with Duke Health Technology Solutions, is implementing commercial solutions for increased medical device interoperability and unified communication (Project Symphony). This will integrate high-resolution physiologic (including waveform) patient data with real-time analytics and present clinicians with a visual indicator of increasing risk of clinical deterioration due to subacute, potentially catastrophic illnesses. A pilot will start in the adult cardiothoracic surgical service line (CTOR, CTICU, and CT SDU beds) in early 2021. For effective implementation, we will partner with existing DUHS structures (Maintenance of Certification and Stakeholder Groups) ultimately enable us to assess the effect of human-centered augmented intelligence on clinical team performance in response to clinical deterioration.

ACADEMIC OUTPUT

Four abstracts/posters were presented nationally (see below). The manuscript is under preparation.

Cortina G, Zhong S, Nichols M, Gao M, Ratliff W, Knechtle W, Balu S, Kester K, Lindsay M, Engle J, Bhatta A, Schroder J, Henao R, Sendak M, Podgoreanu M. Development and Validation of a Machine Learning Model to Predict ICU Readmission or Mortality After Discharge From the Cardiothoracic ICU. Presented at the Annual Meetings of the International Anesthesia Research Society, the Association of University Anesthesiologists, the Society of Critical Care Anesthesiologists, and 2020 Machine Learning for Healthcare conference. August 8, 2020; formerly Durham, NC (virtual).

Table 2. Performance characteristics of machine-learning predictive models compared to logistic regression and standard of care early warning scores.

MODEL (48-HOUR RETURN TO ICU)	AUROC	AUCPR
Logistic Regression	0.70	0.08
Gradient Boosted Decision Trees	0.74	0.11
MODEL (14-DAY RETURN TO ICU)		
Logistic Regression	0.85	0.40
Gradient Boosted Decision Trees	0.83	0.36
SCORE ASSESSMENTS		
NEWS	0.58	0.03
MEWS	0.57	0.03
TOP PREDICTING FEATURES FROM LOGISTIC REGRESSION		
Number of Comorbidities	Immunizations and ID Screening	
History of pneumothorax	Std. of DBP in ICU	
WBC count	Minimum pulse oximetry	
IV fluid administrations	Minimum SBP	
CTICU admissions (past 3 mo.)	Mean sodium in OR and ICU	

DIHI PERSPECTIVE

Seeing and responding to COVID-19

Will Knechtle, MBA, MPH

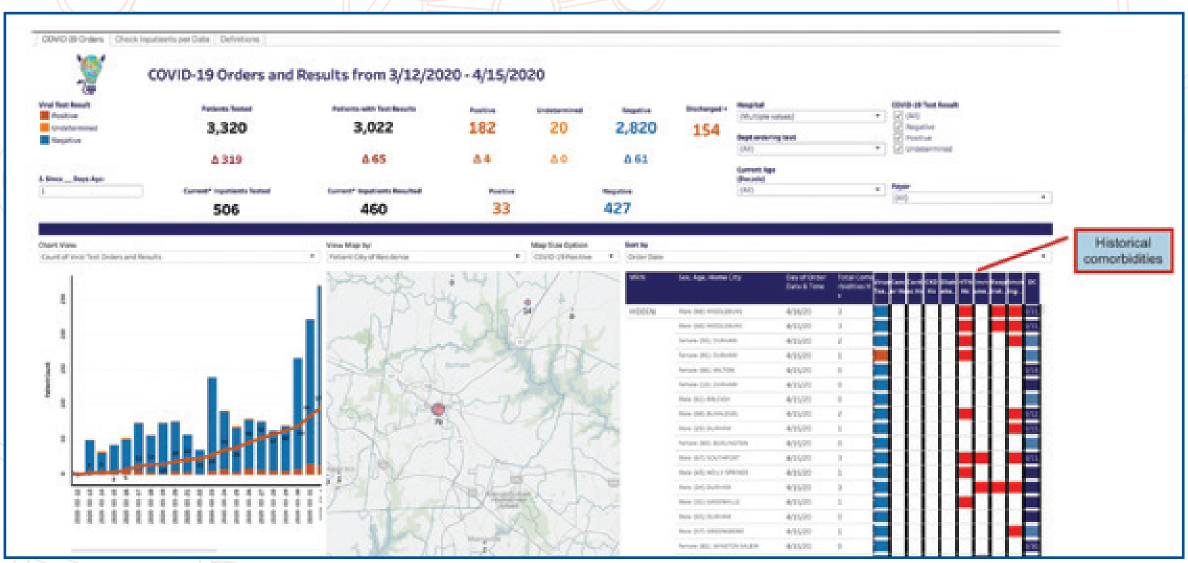
The COVID-19 pandemic illuminated the necessity of effective health information communication. Anyone evaluating the impact of SARS-CoV-2 and preparing for COVID-19 needed accurate data quickly—and they needed to persuade others with the resulting messages. When COVID-19 cases were identified in North Carolina, the Duke Institute for Health Innovation (DIHI) found itself in a unique position to serve Duke Health with real-time data and implementation science. On March 13, the DIHI team began working around the clock to continuously curate and monitor new and evolving influenza and COVID-19 lab tests, test results, and demographic data while visualizing these data within dashboards.

DIHI had a strong foundation upon which to curate actionable COVID-19 data. Members of the DIHI team were already implementing trustworthy and responsible augmented intelligence solutions through projects like SepsisWatch.

Furthermore, principles of epidemiology visualizations had developed since the time of John Snow and William Farr, who curbed a 1800s cholera epidemic by using models and maps to relate statistics to the world. Projects previously implemented by DIHI had reiterated that, for data science to improve healthcare, data should be made actionable and this is achieved through visualizations that are timely, accessible, and easily interpretable.

“Facts, however numerous, do not constitute science. Like innumerable grains of sand on the seashore, single facts appear isolated, useless, shapeless; it is only when compared, when arranged in their natural relations, when crystallized by the intellect, that they constitute the eternal truths of science.”
– William Farr, Epidemiologist, 1837

Figure 1. COVID-19 dashboard combining summary counts, result trends, map, and comorbidity table.



Our next step at DIHI was to apply these principles to real-time COVID-19 dashboards.DIHI's COVID-19 dashboards had to make information accessible. When working with interactive data visualization software, the opportunities to explore a visual through clicks and hovers felt unlimited. However, data became more accessible when the user needed fewer clicks to see everything they needed (Figure 1).

We designed our dashboard to provide the optimal amount of content to facilitate decision making in a fast-paced environment. However, balancing user convenience with data lucidity was important. Accessible data consumption demanded efficient graphics placement, formats, and styles. To make data both accessible and understandable, we deliberated design tradeoffs with data content, and we worked constantly and iteratively to incorporate feedback from real world consumers of the dashboard, primarily frontline clinicians and administrators.

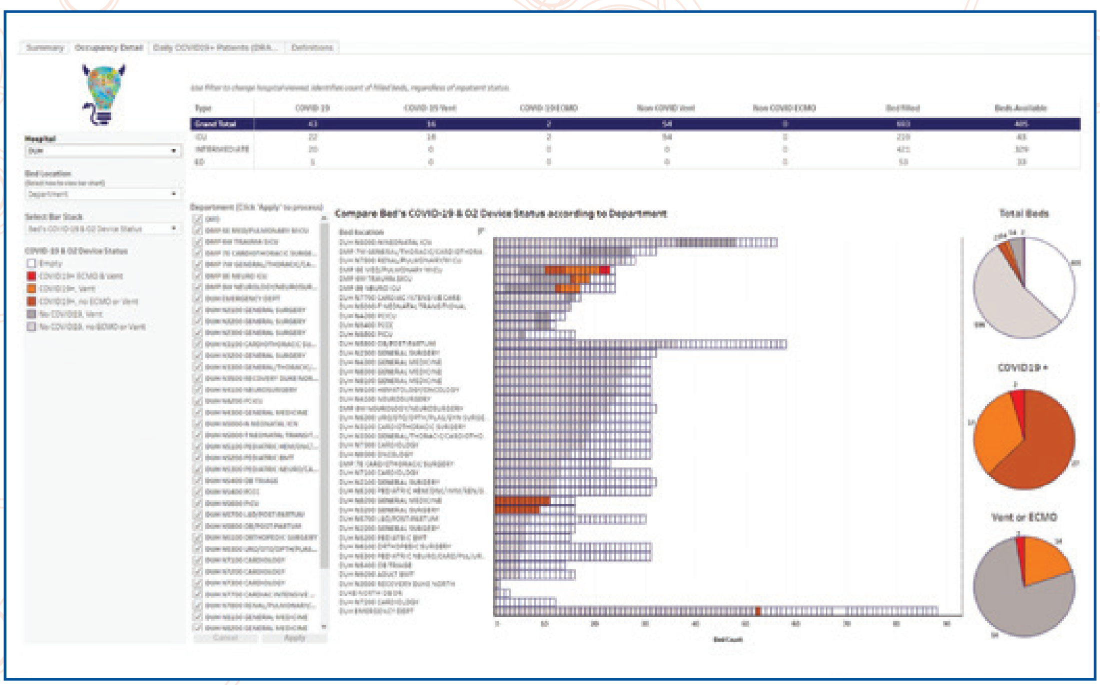
This process of iteration and improvement helped to ensure that our data were not only understandable but also usable and actionable. We communicated multiple times daily with Duke Health COVID-19 Task Force leaders to identify evolving needs, meet expectations, and validate accuracy.

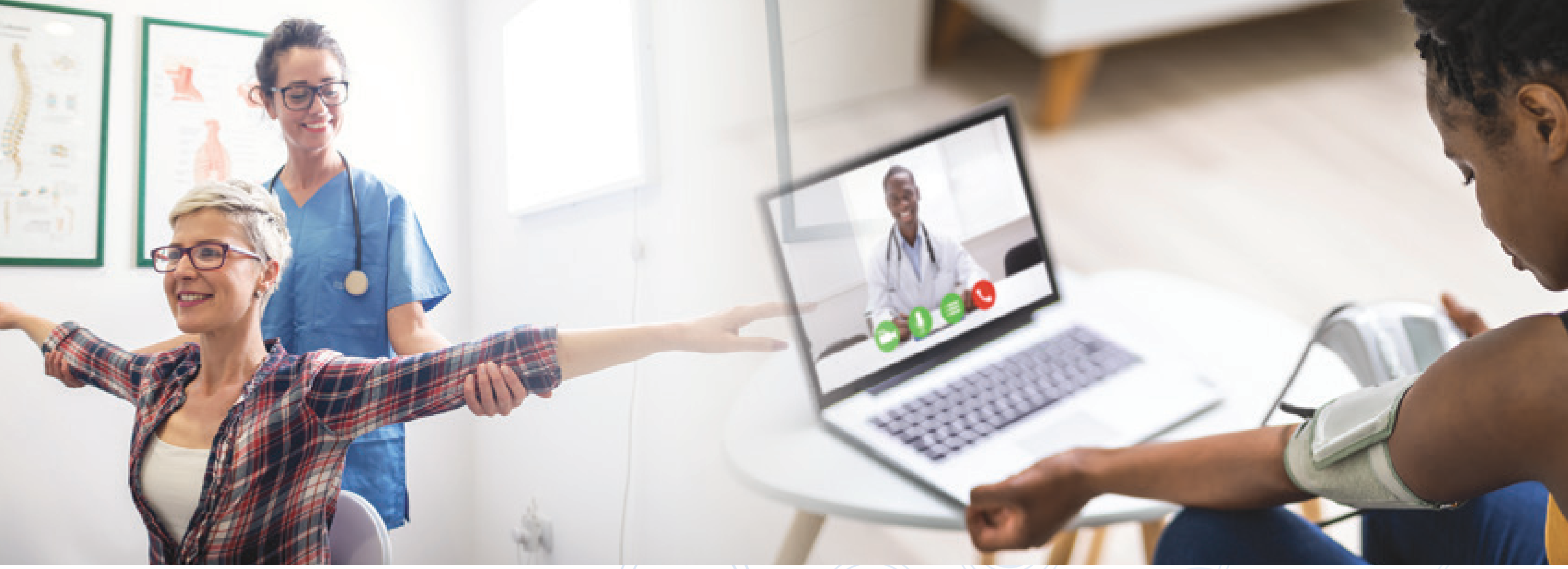
As a result, we were among the first in early March to identify a local COVID-19 hotspot, call leaders in our network, and relay the message to public health leadership.

Much as John Snow and William Farr made their models actionable with maps of water pumps in the city, we made COVID-19 data actionable by real-time charting of patient bed status (Figure 2). Clear communication enabled our stakeholders to ensure we built transparent and actionable dashboards that led to systematic COVID-19 identification and treatment protocols.

In 2020 the world was asked to understand and follow a simple message: wash hands, wear masks, and socially distance. Despite the simplicity of the message, consistently communicating, understanding, and adhering to that message has been anything but simple for our society. Reflecting on reactions to COVID-19, we learn just how accessible the output augmented intelligence solutions must be in order to be actionable and, consequently, impactful. Partnering with machines might be the simplest part, while most of the effort lies ahead in partnering with people. We hope you can observe the great strides that DIHI has made in these partnerships.

Figure 2. Real-time COVID-19 dashboard summarizing bed capacity and locations of beds of patients with COVID-19 and O2 devices. Hovering a mouse over pie slices or squares (beds) revealed further detail.





TELE-EXAMINATION FOR ROTATOR CUFF TEARS

Comparison of the Accuracy of Telehealth Examination Versus Clinical Examination in the Detection of Rotator Cuff Tears

In 2017, the American Orthopaedic Association advocated for the increased use of telehealth as an assessment and treatment platform, and demand has significantly increased during the COVID-19 pandemic. Prior to COVID-19 and afterward, telemedicine is a platform that can increase access for patients lacking subspecialized shoulder care. Diagnostic effectiveness (also called overall diagnostic accuracy) and reliability of a telehealth clinical examination versus a traditional shoulder clinical examination (SCE) has not been established. Our objective was to compare the diagnostic effectiveness of a telehealth shoulder examination against an SCE for rotator cuff tear (RCT), using magnetic resonance imaging (MRI) as a reference standard. Secondary objectives included assessing agreement between test platforms and validity of individualized tests.

We hypothesized that tests provided in a telehealth platform would not have inferior diagnostic effectiveness to an SCE. By establishing this, we plan to expand the use of telehealth as a valid screening tool for assessment of common shoulder pathology and to implement these examination techniques in clinical care.

TEAM

Jocelyn Wittstein, MD; Anne Boyd, CNMT, RT(R)(N); Alex Cho, MD, MBA; Chad Cook, PT, PhD, MBA; Tally Lassiter, MD, MHA; Chad Mather, MD, MBA; Donna Phinney, RN; Emily Reinke, PhD; Shilpa Shelton, MHA; Emily Vinson, MD; Kendall Bradley, MD; Will Ratliff, MBA; Will Knechtle, MBA, MPH

PROJECT IN BRIEF

Subspecialized care is lacking in rural areas and patients prefer to travel less than 30 kilometers. We developed, tested, and validated shoulder telehealth examination protocol to properly indicate patients for MRI, and ultimately procedures. This increased access to care and improved population health.

SOLUTION

Development and testing of overall diagnostic accuracy of a telehealth shoulder examination was completed to establish a model for telehealth evaluation of atraumatic shoulder pain that can now be implemented in clinical practice and allow further research into patient satisfaction, cost effectiveness, and clinical decision making.

The study is a case-based, case control design. Two clinicians selected movement, strength, and special tests for the standard SCE that are associated with diagnosis of RCT and identified similar tests to replicate for a simulated telehealth-based examination (STE). Consecutive patients with no prior shoulder surgery or advanced imaging underwent both the SCE and STE in the same visit using two separate assessors. We randomized the order of SCE or STE.

A blinded reader assessed an MRI to use as a reference standard. We calculated diagnostic effectiveness, which provides values from 0% to 100% as well as agreement statistics (Kappa) between tests by assessment platform, and sensitivity, specificity, and likelihood ratios for individual tests in both SCE and STE. We compared diagnostic effectiveness (overall) of SCE and STE with a Mann-Whitney U test.

OUTCOMES

We included 62 consecutive patients with shoulder pain, aged 40 or older; 50 of these (81%) received an MRI as a reference standard. Diagnostic effectiveness of stand-alone tests were poor regardless of the group, with the exception of a few tests with high specificity. None had greater than 70% accuracy. There was no significant difference between the overall diagnostic effectiveness of the STE and the SCE (p=0.98). Overall agreement between the STE tests and the SCE tests ranged from poor to moderate (Kappa 0.07-0.87). This study identified initial feasibility and noninferiority of the physician-guided, patient-performed STE when compared to an SCE in detection of RCTs.

The examination techniques used in this study are being incorporated in telehealth encounters for new shoulder patients and may increase the geographic footprint of healthcare networks; it may also increase providers' opportunities to evaluate patients in the midst of a pandemic. Future studies are underway to test the accuracy of STE for different shoulder pathology and assess clinical decision making based on STE.

NEXT STEPS

The next step is to continue to expand clinical use of telehealth for new and return shoulder visits as well as postoperative care of rotator cuff patients. While study of safety, satisfaction, and cost savings of postoperative care via telehealth after cuff repair is a next step project, it is not currently the focus of future grant submissions. Future grant applications will focus on clinical decision making based on the telemedicine platform.

As an initial step to this end, we are planning a clinical decision making vignette study based on the actual history and exam findings from the two platforms (in person versus telemedicine examination findings), with the hypothesis being that the two examination platforms will result in similar clinical decision making.

ACADEMIC OUTPUT

The grant cycle for the Rockwood Clinical Research Grant in Shoulder Care opened in Nov. 2020 and was established as a next target at the time of this article's writing. Focus of future grant-funded work will be on clinical decision making using a telehealth platform for evaluation of atraumatic shoulder pain. Upon review of clinicaltrials.gov, clinical studies of satisfaction with telehealth visits and care models are now numerous due to COVID-19, but studies of diagnostic accuracy and clinical decision making are lacking and necessary.

Bradley, K. E., Cook, C., Reinke, E. K., Mather, R. C., 3rd, Riboh, J., Lassiter, T., & Wittstein, J. R. (2020). Comparison of the Accuracy of Telehealth Examination versus Clinical Examination in the Detection of Shoulder Pathology. *Journal of shoulder and elbow surgery*, S1058-2746(20)30689-3. Advance online publication. https://doi.org/10.1016/j.jse.2020.08.016

Winner, best paper, J. Leonard Golder Research Day 2020

EARLY DETECTION OF CLINICAL DETERIORATION

Saving Lives Through Early Detection of Clinical Decompensation

Patients often show early signs of deterioration hours before a rapid response team (RRT) or code blue is activated, and delays in care can have a detrimental impact on clinical outcomes. Specifically, patients who are transferred unexpectedly to the intensive care unit (ICU) often have worse outcomes and increased mortality compared with patients with a planned ICU admission. While it is vital that deterioration is identified early to prevent adverse outcomes, we have an opportunity to improve our ability to predict and intervene in the care of patients at risk of deterioration in real-time.

SOLUTION

Duke University's Department of Medicine and the Duke Institute for Health Innovation formed a transdisciplinary team to develop a machine-learning model to accurately predict a patient's risk of unanticipated ICU transfer or inpatient mortality. We began by curating data from 174,314 adult patient hospital encounters (age >=18 at hospital admission) from Duke's three hospitals between October 2015 and August 2018. The outcome was defined as the time of an unplanned transfer to the ICU.

TEAM

Cara O'Brien, MD; Stephanie Skove, BS; Harvey Shi, BS; Ziyuan Shen, MS; Michael Gao; Mengxuan Cui, MS; Marshall Nichols, MS; Armando Bedoya, MD; Dustin Tart, BSN; Benjamin A. Goldstein, PhD; Will Ratliff, MBA; Mark Sendak, MD, MPP

PROJECT IN BRIEF

We incorporated four years of data from across the Duke Health enterprise to identify deterioration events for patients in the hospital. We then created a deep learning model to predict these events within 48 hours. We are now piloting a solution in partnership with the Patient Response Program team to identify and intervene on these patients earlier.

Direct transfers from the emergency department to the ICU or from the operating room to the ICU were not included as unplanned ICU transfers. Additionally, we excluded brief ICU admissions, where patients spent <90 minutes in the ICU before being transferred to a different level of care. We observed 4,775 unique transfer-to-ICU events. For model inputs to predict this outcome, a total of 565 features were built from 83 electronic health record data elements, including comorbidities, demographics, historical features (such as prior hospital encounters), vitals, labs, orders, and medication administrations.

We trained the deep learning model to predict the outcome on the 2015-2018 cohort, and then evaluated it on January 2019 through December 2019 adult inpatient hospital encounters. For each encounter trained and evaluated, we split the encounter's total hours into four-hour windows leading up to the ICU transfer.

OUTCOMES

Our team successfully developed a solution to intervene proactively on patients as they begin to deteriorate. It features a deep learning model that accurately predicts the refined outcome of unanticipated ICU transfer within the subsequent 48 hours. The model was evaluated on 66,838 unique inpatient encounters across the three hospitals. These encounters yielded 1.8 million four-hour windows, of which 19,844 windows (1.1%) resulted in an ICU admission within the subsequent 48 hours. At the window level, the deep learning model had an AUROC of 0.91 and an AUPRC of 0.14. At the encounter level, the model achieved a precision of 0.226 at a threshold of 0.95.

With this model, we created a real-time Tableau dashboard to display risk scores for all adult patients currently hospitalized at Duke University Hospital, Duke Raleigh Hospital, and Duke Regional Hospital. New predictions are generated and displayed on the dashboard every hour, along with other key data to contextualize the deterioration risk. The clinical leads evaluated the model's output on snapshots of patients recently admitted to one of the hospitals. Concurrently, the project team finalized the pilot workflow in partnership with the Patient Response Program (PRP) team. We plan to pilot the workflow plus dashboard solution beginning in late 2020 at Duke University Hospital, and evaluate its impact on ICU transfers, length of stay, and other outcome metrics at the end of the pilot period in spring 2021.

NEXT STEPS

During the pilot period, we hope to gain additional insights to optimize the solution, which we will incorporate into a planned expansion to Duke Raleigh Hospital and Duke Regional Hospital. Incorporating guidance from key stakeholders, we plan to tailor the dashboard and the workflow to best support proactive deterioration monitoring and interventions at these locations. Additionally, we are optimizing our alert mechanisms, including the use of timely push notifications, to minimize burden on our care providers while supporting them in delivering high quality care to patients at Duke.

ACADEMIC OUTPUT

Skove S, Shi H, Shen Z, Gao M, Cui M, Nichols M, Balu S, Bedoya A, Tart D, Goldstein B, Ratliff W, Sendak M, O'Brien C. Development of Machine Learning Model to Predict Risk of Inpatient Deterioration. Poster presented at: Machine Learning for Healthcare 2020. August 8, 2020; formerly Durham, NC (virtual).

DIHI PERSPECTIVE

Responding to COVID-19: Handling Broken Fragments of American Healthcare

Mark Sendak, MD, MPP

In 2013, one of my favorite health policy professors described the Affordable Care Act (ACA) as a roll of duct tape. The ACA, the largest piece of healthcare legislation enacted in the United States in decades, took a broken system and taped it back together. It did not address any of the core problems inherent within the system. The fee-for-service payment model continued to prevail, states could continue to leave millions without expanded health coverage under Medicaid, and social and health services would continue to be fragmented and siloed. The duct tape was no match for COVID-19, which has effectively smashed apart American healthcare.

prn

PANDEMIC RESPONSE NETWORK

On Thursday, March 5, I joined a 30-minute call to discuss how our team at the Duke Institute for Health Innovation could help prepare Duke Health for COVID-19. By the following Monday, March 9, I spoke with the DIHI team director about COVID-19 potentially being the greatest and most important challenge in our team's existence. We had to rise to the occasion to support our community, our institution, and the broader population. And we did. Our experience building partnerships within and beyond Duke to help launch and lead the Pandemic Response Network has been transformative.

Over the last eight months, we have stood up programs to help the general public, Duke University campus community, and Duke Health worker community—and thousands of people use these programs daily. We are now working to adapt these technologies and workflow systems to support schools, businesses, and entire municipalities.

Thousands of people at Duke, in Durham, and across the country use tools we built and every day, people interact with clinicians we helped train to support individuals through the pandemic. We have forged relationships with religious leaders in historically marginalized communities that lack access to health and social services, as well as relationships with large investment firms with billions of dollars in managed assets. We have met with public officials at the city, county, state, and national level across both health and education sectors. With our partners, we have secured millions in state funding to support community health workers and community-led COVID-19 support programs and have applied for millions more. We are helping build back better, filling critical gaps in infrastructure that existed long before COVID-19 and continue to stifle our national response to the pandemic.

Three lessons have emerged over the last eight months that we ground our work in. First, we need to work both within and beyond the bounds of formal institutions. A local Latina community organizer who we have been working closely with during the pandemic gave us the early advice to "look outside institutions." She helped us identify the local grassroots movements that were already organizing to meet the needs of historically marginalized communities.

Her insights were the manifestation of findings from our collaboration with IDEO.org that:“Oak trees don’t set an intention to listen to each other better, or agree to hold tight to each other when the storm comes. Under the earth, always, they reach for each other, they grow such that their roots are intertwined and create a system of strength that is as resilient on a sunny day as in a hurricane.”

We now work directly with church and community leaders to onboard and manage community health worker programs that reach historically marginalized communities in new ways. We are gradually removing the barriers that prevented many of these individuals and communities from being able to access healthcare.

We have learned to start where we have alignment—where people feel comfortable. Then, we undertake the hard work of accompanying people and communities through the pandemic.

Second, we need to continue to grow and adapt our coalition. The tapestry of actors who have supported and empowered the Pandemic Response Network is vast. A general partner at a top venture capital firm keeps in touch with potential ideas and connections to expand and enhance the work. A social scientist at a large tech company has helped us understand how our work is differentiated from efforts in other states and helps us communicate about our work and connect to potential funding sources and public sector partners. Dozens of students and trainees at Duke University have responded to a call for volunteers to make thousands of phone calls to individuals across the country in need of support. Our champions include clinicians, community members, lawyers, church leaders, business executives, construction workers, and individuals from across all walks of life, both within and beyond Duke. The lack of a coordinated federal response to COVID-19 has been met with the incredible force of individuals connecting with each other to coordinate a response.

Third, we need to focus on both adding spaces to existing tables as well as setting up new tables for individuals and communities who have been left behind by American healthcare. The exercise is similar to planning seating for a wedding reception, where the number of tables and makeup of each table is far more important to attendees than the overall head count. The COVID-19 pandemic has demonstrated to us all that a public health crisis coupled with a communication crisis leaves factions of individuals with drastically different lived experiences and perceptions of events. In addition, many individuals face significant economic, psychological, and health hardships, magnifying the intensity with which individuals hold onto ideas and reasoning that brings them comfort. Rather than focus on trying to change perceptions to bring two groups to sit at one table, it can be okay to set up two tables. We have learned to start where we have alignment—where people feel comfortable. Then, we undertake the hard work of accompanying people and communities through the pandemic.

While we are incredibly proud and invigorated by our work over the last eight months, we have a long road ahead. The communities we work with continue to harbor strong distrust of health and public institutions. An African American church leader recently told us, “I ain’t taking a vaccine until I watch white folk take it and not drop dead.” We continue to be open to the voices and stories of our partners and continue to learn about ways to enhance and improve our work. We look forward to increasing the number of private and public partners we engage and to continuing to launch COVID-19 support programs that empower workers, communities, and students.

We remain committed to our mission to help people stay safe and connected and invite you to join us in this journey. We invite you to join us as we build and enhance the Pandemic Response Network.

To learn more about how you can join us, please visit our English and Spanish pages:
https://pandemicresponsenetwork.org/

https://pandemicresponsenetwork.org/covidwatch-es

ENHANCING VBC THROUGH TRANSPARENCY

Understanding Underlying Healthcare Costs for Hernia Repair to Deliver Value-Based Care

In the United States, healthcare costs are absorbing larger portions of our Gross Domestic Product (GDP) year over year. In 2018, healthcare spending grew 4.6% to $3.6 trillion and accounted for 17.7% of U.S. GDP. Healthcare systems, including Duke, must share in the responsibility of controlling costs as providers transition to value-based care (VBC) and take on downside payment risk. However, we must not allow these cost-saving measures to diminish the quality of care for our patients. To deliver the highest quality, low cost care to our patients, we must understand the detailed cost components and patient outcomes in order to isolate and eliminate unnecessary costs associated with delivering that care.

TEAM

Julie Doberne, MD, PhD; John Rollman; Josh Watson, MD; Dave Thompson, MD; Wendy Webster, MBA; Gary Faerber, MD; Will Ratliff, MBA

PROJECT IN BRIEF:

We created a value-based scorecard for inguinal hernia repair surgeons at Duke to understand total cost of care as well as cost component breakdown by surgeon. We used this tool to guide interviews with hernia surgeons, who then made informed decisions to reduce unnecessary costs associated with their surgeries and shared insights on opportunities for institutional cost savings across Duke Health for hernia repair.

SOLUTION

Duke University's Department of Surgery collaborated with the Duke Institute for Health Innovation to design a dynamic, value-based scorecard for inguinal hernia repair (IHR) surgeons to understand the total cost of the care they delivered, including a detailed cost breakdown of costs and patient outcomes by surgeon. Hernia repair was chosen as a pilot use case due to its relatively consistent surgical approach and stable patient outcomes.

The project team began by categorizing and comparing cost components by surgeon at each location, within the open and laparoscopic hernia repair case types. Applying this understanding, the team created the Hernia Cost of Care Dashboard in Tableau, including cost overview, provider-level costs, and supply-level costs per case. The dashboard's dynamic functionality featured costs across location, costs compared to time spent on the case, teaching versus non-teaching categorization, costs compared to patient outcomes, and a comparison of cost line items per case type for a given surgeon versus his/her peers.

OUTCOMES

The project team interviewed nine hernia surgeons, who collectively performed over 80% of the annual hernia surgical cases across Duke Health. Using the Hernia Cost of Care Dashboard to guide discussion, the team walked each surgeon through a detailed review of the costs associated with his/her surgical cases as well as available patient outcome data. The team first reviewed location volumes and total direct cost by procedure type (laparoscopic versus open) with the surgeon, as well as a scatter plot of costs compared to time in the operating room for each case, toggling between teaching and non-teaching cases. Then, the team focused on provider-level cost category comparisons of the surgeon and his/her peers: hospital supply costs, hospital labor costs, operating room supply costs, drug costs, and equipment costs. Finally, the team used the dashboard to break down these categories into the individual cost drivers, in order to compare a surgeon and his/her peers performing the same procedure type.

The surgeons gave overwhelmingly positive feedback on the detail and clarity of approach, stating that this tool helped them make informed decisions about the costs of their cases. One-third of the surgeons committed to removing unnecessary costs as identified by the dashboard during the interview itself, resulting in thousands of dollars in annualized savings to the health system. Moreover, the surgeons shared insights regarding cost-saving considerations for institutional adoption at Duke, based on their experiences as confirmed by what they were seeing broadly from the dashboard.

NEXT STEPS

With the surgeons' feedback and the findings derived from the dashboard, the team has developed key recommendations to reduce unnecessary costs and streamline care for hernia repair at Duke. Under the guidance of the Duke Department of Surgery, these recommendations will be carried forward to reduce variability of supplies across locations; streamline supply menus to those supported by surgeons that cost less and yield high quality patient outcomes; and disseminate preferred low cost, high quality outcome approaches to hernia repair at Duke. The dashboard methodology and interview process are now being applied to investigate other surgical use cases, supporting Duke in providing the highest quality of care while reducing unnecessary costs.

DIHI INNOVATION SCHOLAR PERSPECTIVE

Zohaib Shaikh

I sought out the Duke Institute for Health Innovation (DIHI) scholar experience because I was looking for an opportunity to step outside of traditional clinical medicine and engage in truly innovative research. During my clinical clerkships, I had participated in excellent care that positively impacted patients' lives. Unfortunately, I had also seen some patients deteriorate when perhaps closer attention, earlier detection of their decline, and prompt intervention could have led to better outcomes. I recognized the need for innovative, systems-level changes that make it as easy as possible to provide effective care and make it difficult for patients to end up in harms' way. One way I wanted to accomplish this was by mobilizing and transforming the massive amount of data logged in the electronic health record (EHR) in order to use it to improve patient care.

At DIHI, I had the privilege to work on an interdisciplinary team to develop machine learning models to predict clinical deterioration in pediatric patients. Early in the process, I worked with my team members to curate relevant data elements from the EHR while I studied Python and SQL, both of which were new to me. Eventually, I was working comfortably enough on complex code to carefully structure large datasets and apply machine learning techniques to generate useful predictions from massive amounts of data.

In some ways, I served as a bridge between two fields, equipped with a growing understanding of both medicine and data science. This helped me take on a lead role and drive this project through its early development to implementation. Along the way, I learned how to effectively partner across disciplines to pioneer an innovative project that can be implemented into actual clinical practice. Our early results were promising, and I hope our model will one day be integrated into the inpatient workflow and prevent children from having poor hospital outcomes. Armed with the lessons I learned during my time at DIHI, I hope to be at the forefront of enhancing patient care through innovation as a future physician and budding data scientist.

DIHI PERSPECTIVE

Extending Impact Reporting through Sepsis Watch Evaluation

Will Ratliff, MBA, and Bradley Hintze, PhD

Artificial intelligence (AI) in healthcare has been around for a few years, but many challenges remain. Chief among these is how to evaluate the effectiveness of an AI solution. At Duke, we are trying to address this head-on in our assessment of Sepsis Watch on patient care. We can't (yet) share all of the details on patient outcomes, as we are completing our internal evaluation with the goal of publication in early 2021. However, we can preview our approach to this evaluation and summarize the observational data related to sepsis care interventions, specifically the sepsis bundle compliance as adjudicated and reported by Duke to the Centers for Medicare & Medicaid Services (CMS).

Every year, roughly 1.7 million American adults develop sepsis, with 270,000 dying as a result of the disease. To address this challenge at Duke, we collaborated with clinical, technical, and operational colleagues to bring Sepsis Watch live on November 5, 2018 at Duke University Hospital and subsequently at Duke Raleigh Hospital and Duke Regional Hospital in June 2019. Each hospital began as a six-month pilot period with a unique workflow and distinct set of interactions with Sepsis Watch to support that workflow.

That said, the setting and cohort for whom Sepsis Watch was intended remained consistent: Sepsis Watch aimed to support rapid identification and treatment support for emergency department (ED) patients at high risk of sepsis. Looking forward to today, each location has further adapted and developed supportive infrastructure to maintain the solution as a valuable data point for early intervention on septic patients. However, as each location continues to evolve to face new challenges, especially in the COVID-19 era, the question remains: is Sepsis Watch as a solution (machine learning model + application + workflow) having a meaningful impact on patient care?

Observationally, we see a promising trend in the SEP-1 bundle compliance, a metric used by CMS to compare quality of sepsis care across hospitals. It is measured each quarter via an adjudication of a random sampling of patients who were diagnosed as septic at some point during the encounter. When we look at average bundle compliance two years pre-implementation versus implementation (which began in Nov. 2018) through last quarter (Q2 2020), we see significant performance improvement at all three hospitals: a 110% improvement at Duke University Hospital, a 45% improvement at Duke Regional Hospital, and a 133% improvement at Duke Raleigh Hospital. However, while the Sepsis Watch application is designed to support bundle completion tracking, it is perhaps most important to evaluate whether this solution is having an impact on patient outcomes.

*Every year, roughly **1.7 million** American adults develop sepsis, with **270,000 dying** as a result of the disease.*

Our goal is to illustrate this impact through specific quality of care metrics, including in-hospital mortality, hospital length of stay, whether escalation of care to the intensive care unit (ICU) was required, and, if so, ICU length of stay. We first identify cohorts for each hospital, pre- and post-Sepsis Watch implementation. Included are patients who enter the ED and met the definition of sepsis in the ED. We determine that the patient is septic using three distinct definitions: the real-time Sepsis Watch definition, diagnosed as septic by a physician, and the CDC's retrospective Adult Sepsis Event (ASE) definition. Because the latter definition is considered a gold standard for defining time of sepsis, we consider it a key milestone in our analysis. We plan to further apply this definition automatically into the Sepsis Watch workflow and other efforts involving deterioration.

The development of this evaluation is allowing us to expand our clinical and technological knowledge. We are creating new methods to generate reproducible techniques and phenotypes, which allows us to expedite and extend the impact analysis. New questions naturally arise via this process, and therefore, we may add more outcomes to analyze or need small tweaks to analysis methods. To make such a process as painless as possible, we are employing a MongoDB database to house all relevant encounter data for this large cohort. MongoDB is a document store allowing all data from each encounter to be stored together.

*When we look at average bundle compliance two years pre-implementation versus implementation (which began in Nov. 2018) through last quarter (Q2 2020), we see significant performance improvement at all three hospitals: a **110% improvement** at Duke University Hospital, a **45% improvement** at Duke Regional Hospital, and a **133% improvement** at Duke Raleigh Hospital.*

With this foundation in place, we can make both small changes and large additions to the impact analysis, and the subsequent data pull from MongoDB can be measured in minutes rather than days. Further, the analysis automates the creation of a cleanly formatted PDF report. This makes the results immediately accessible to all stakeholders. With the copious amount of time saved, we plan to apply this approach to our future impact reporting. Moreover, we hope to lead the effort in developing frameworks, methods, and tools in assessing AI solutions on impactful patient outcomes.

DIHI INNOVATION SCHOLAR PERSPECTIVE

George "Bert" Cortina

During my year at the Duke Institute for Health Innovation (DIHI), I primarily worked on a project predicting post-operative patient decompensation. First, we predicted which patients were at the highest risk of returning to the ICU or dying in the next 14 days. This aids in deciding who is ready to leave intensive care for a lower acuity (step-down) unit. Second, we worked toward developing an alert model for step down units to predict who is most likely to die or return to the intensive care units within the next 48 hours. I played a key role in integrating the data, which gave me an understanding of the aspects involved with using machine learning for answering medical questions.

I came to DIHI from the University of Virginia, for the last year of my MD-PhD training. In my PhD, I had worked to predict how amino acid mutations affected drug resistance to antibiotics. This worked involved computational statistics and machine learning.

After my PhD, I sought to apply these techniques to patient data to answer questions and build solutions that directly affect healthcare. DIHI's dual focus of answering complex questions with machine learning along with implementing these findings in the hospital was exactly what I wanted for the next step of my training. UVA and DIHI were both incredibly helpful in making this a possibility and this proved to be an amazing experience.

Moving into any new area of research can always present challenges, and DIHI offered a variety of expertise and teaching which greatly developed my skills. Now, as an anesthesiology resident at Duke, I look forward to future research projects and using machine learning to improve patient care.

PROJECT UPDATE: EARLY IDENTIFICATION OF CARDIAC DECOMPENSATION

Creating Digital Phenotypes to Identify and Predict Decompensation in Cardiology and Across the Hospital

The cardiac decompensation project began as a proposal for the DIHI RFA 2018 round, wherein Dr. Ajar Kochar and the Duke Heart Center aimed to develop a machine learning model to predict cardiogenic shock and an associated workflow to intervene on high risk patients. As the project evolved, we learned that this deadly condition causes a 21% to 30% in-hospital mortality rate for patients at Duke. We also learned more about the myriad drivers of cardiogenic shock, so we pivoted to focus earlier and think more broadly about the deterioration progression in these patients.

Armed with complete data and with the guidance of our clinical leads, we iteratively refined six definitions of clinical deterioration, our cardiac decompensation phenotypes (Table 1).

Specifically, we applied patient encounter real-time data to define the following phenotypes: hypotension, end organ dysfunction, hypoperfusion, vasoactive medication administration, respiratory decline, and respiratory intervention.

TEAM
Will Ratliff, MBA; Harvey Shi; Michael Gao, MS; Mark Sendak, MD, MPP; Stephanie Skove; Sicong Zhao, MS; Marshall Nichols, MS; Kelly Kester, MSN; Chet Patel, MD; Schuyler Jones, MD; Cara O'Brien, MD; Aman Kansal, MD; Dennis Narcisse, MD; Ajar Kochar, MD, MHS; Jason Katz, MD, MHS; Manesh Patel, MD; Zach Wegermann, MD

PROJECT IN BRIEF:
We analyzed, validated, and modeled six clinical cardiac decompensation phenotypes, launched a real-time Tableau dashboard to display patients meeting or at risk of meeting those phenotypes, and are now piloting the solution in the cardiology units at Duke University Hospital to improve clinical outcomes.

We then assessed these phenotypes' correlation to adverse outcomes of unanticipated intensive care unit (ICU) transfer and in-hospital mortality. Compared to all hospitalized patients at Duke, who experience ICU transfer and in-hospital mortality in roughly 2.5% of encounters, we found that patients who met at least one of the phenotypes had a 5.9% ICU transfer rate and 5.0% in-hospital mortality rate.

Patients who met all six phenotypes had a 28.9% ICU transfer rate and a 36.5% in-hospital mortality rate. We also found that patients who met a phenotype did so soon after admission, with a range of 3 to 31 hours across the phenotypes between admission time and phenotype time.

Given these quick time-to-detection rates and the rates of adverse outcomes, we refined our models to produce an hourly prediction of a patient's risk of meeting each phenotype individually within the next 12 hours as well as within the next 24 hours.

Table 1: Cardiac decompensation phenotypes

PHENOTYPE	DEFINITION
1: Hypotension	Patient has any of hypotension criteria: 1) two SBP < 90 mmHg within a 6-hour window 2) two MAP < 65 mmHg within a 6-hour window
2: End organ dysfunction	Patient has any of end organ dysfunction criteria: 1) Acute Renal Insufficiency - KDIGO (↑ Creatinine ≥ 0.3mg/dl in 48 hrs, or Creatinine ≥ 1.5x baseline); patient does not have ESRD, is not on dialysis 2) Lactate > 2.0 mmol 3) AST or ALT > 5x ULN (at Duke AST= 205 U/L, ALT = 315) 4) Total Bilirubin > 2.0 mg/dL
3: Hypoperfusion (1 then 2)	Patient has any of hypotension criteria (see above) AND then patient has any of end organ dysfunction criteria within a 24-hour window (see above)
4: Vasopressors	Patient receives new administration or increased dose of vasopressor dopamine; norepinephrine; milrinone; dobutamine; epinephrine; phenylephrine; vasopressin
5: Respiratory decline	Patient experiences any indicator of respiratory decline: 1) increase in O2 (> 2L of O2) within 6 hours 2) O2 saturation falls below 91% (ever) 3) paO2 (arterial) < 60mmHg 4) paO2 (arterial) decrease by 10mmHg from baseline (min over 24 hours)
6: Respiratory intervention	Patient has an intervention for respiratory decline – new documentation of escalation (e.g., ii→iii, iv→vi): i. O2 greater than 6 L ii. Hi Flo iii. Opti Flow iv. Non re-breather v. BIPAP vi. Intubation
Additional criteria: Fever	Patient has a sign of fever: 1) Temperature > 38.3 C 2) Two temperatures > 38 C within a 24-hour window

We also explored specific pairings of phenotypes for intuitive scenarios involving either the clinical deterioration or intervention to prevent that deterioration (i.e., hypotension with vasoactive medication, respiratory decline with respiratory intervention). These results are shown in Table 2. With these phenotypes retrospectively analyzed and modeled, we set up a dashboard in Tableau to display patients who met at least one phenotype in the past 24 hours.

For these patients, data is pulled from Maestro Care every hour and used to assess whether the patient has met the phenotype definitions. If the patient has met the phenotype, the dashboard displays the most recent time the patient met the phenotype.
The dashboard also shows the predictive model results for phenotypes a patient has not met but is at high risk of meeting within the next 24 hours.

Table 2: Performance of 12-hour and 24-hour look-ahead prediction model for clinical deterioration phenotypes.

MODEL	HOURLY PREVALENCE	AUROC	AUPRC
Hypotension 12 hr.	0.0159	0.8317	0.0712
Hypotension 24 hr.	0.0268	0.8070	0.0924
End organ dysfunction 12 hr.	0.0323	0.8299	0.1238
End organ dysfunction 24 hr.	0.0519	0.8127	0.1489
Hypoperfusion 12 hr.	0.0043	0.8421	0.0238
Hypoperfusion 24 hr.	0.0072	0.7988	0.0292
New vasopressor 12 hr.	0.0071	0.8811	0.0643
New vasopressor 24 hr.	0.0117	0.8779	0.1016
Respiratory decline 12 hr.	0.0363	0.8136	0.1475
Respiratory decline 24 hr.	0.0627	0.8083	0.1968
Respiratory intervention 12 hr.	0.0125	0.8978	0.1655
Respiratory intervention 24 hr.	0.0212	0.8836	0.1669
Hypotension_new_vaso 12 hr.	0.0193	0.8555	0.0975
Hypotension_new_vaso 24 hr.	0.0319	0.8423	0.1493
Resp_decline_resp_intervention 12 hr.	0.0381	0.8342	0.1500
Resp_decline_resp_intervention 24 hr.	0.0646	0.8301	0.2247

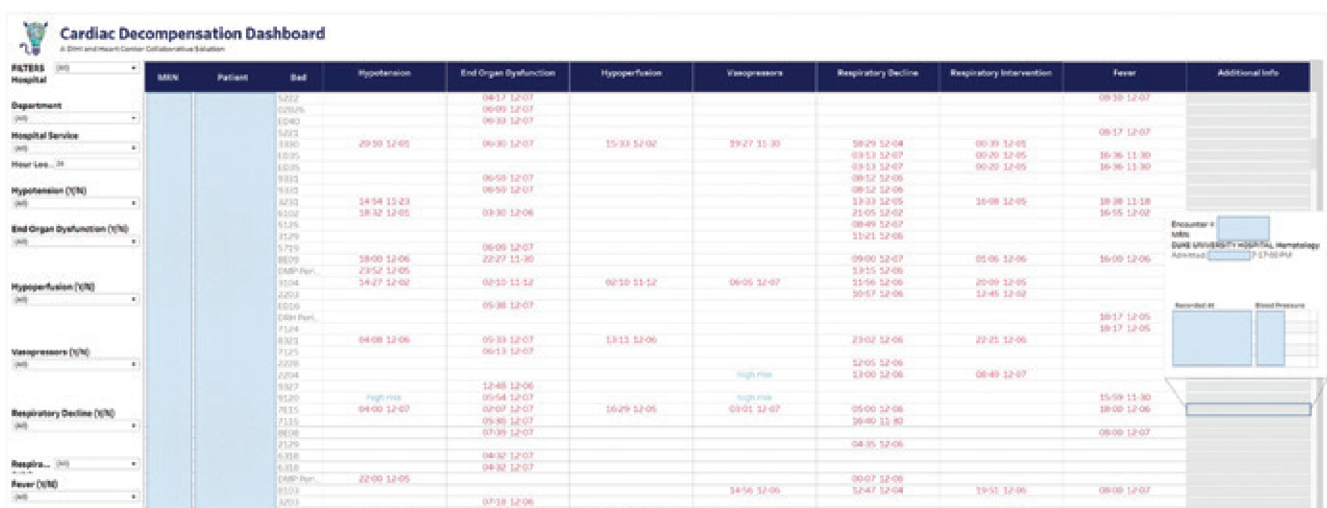
Lastly, the dashboard includes detailed data on what triggered the phenotype event, which users can see when clicking on the “Additional Info” cell for a patient. Figure 1 shows the Real-time Cardiac Decompensation Dashboard.

As a final, crucial step to validate the phenotypes, we evaluated several point-in-time “snapshots” of the patients showing up on the dashboard. Our clinical leads performed a dual adjudication with over 350 phenotype events, including patients across our health system and patients in the cardiology units at Duke University Hospital (DUH). We assessed whether the patient was decompensating at the time of the phenotype timestamp.

We found that over 76% of the phenotype events demonstrated true clinical decompensation of those patients, and that a large portion of non-clinical decompensation events occurred in the perioperative setting. This dashboard is being piloted as part of clinical workflows in all DUH cardiology units. We are developing distinct workflows in partnership with the Cardiology Advanced Practice Provider team as well as with the Patient Response Program team.

Our pilot runs from the end of 2020 through spring 2021, at which point we will assess impact on patient outcomes related to deterioration: hospital length of stay, ICU requirement and ICU length of stay, in-hospital mortality, and rate of Rapid Response Team interventions. We are thrilled to support our frontline care colleagues to more rapidly identify and intervene on Duke patients at risk of deterioration.

Figure 1: Real-Time Cardiac Decompensation Dashboard displays patient clinical phenotype times and predictive model risks, refreshed hourly with patient data from the EHR.



DIHI PERSPECTIVE

Pythion, a Machine Learning Interface Tool for Improving Surgery Outcomes

Harvey Shi

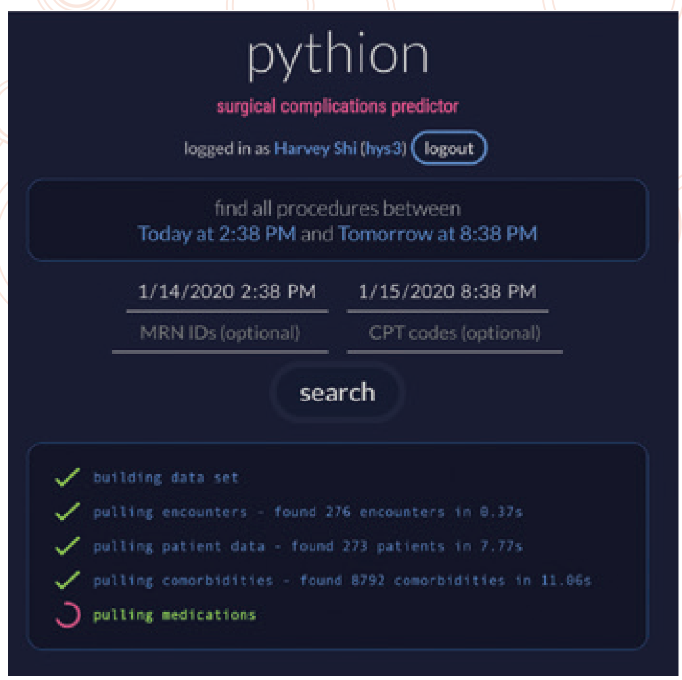
I began working on the Pythion project as my first project at the Duke Institute for Health Innovation (DIHI). Pythion is a set of clinical decision support models for predicting complications with surgical procedures. The models are integrated with the DIHI pipeline and served as a web application and Tableau dashboard. This project was a continuation of the earlier Pythia work by the DIHI team, in partnership with the Duke Department of Surgery and Department of Anesthesiology. Pythia was renamed to Pythion after the project was rewritten using the Python programming language.

With the Pythion project, I was eager to begin learning more about the intersection of medicine, machine learning, and data science. Coming in with a high-performance computing and visualization background, I had some sense of the challenges of working with massive datasets and extracting useful information; however, building and deploying clinical models presented an unexpected set of challenges.

My first step was data curation. I began by going through all the data elements that had been included previously by the Pythia team, adding new features and expanding the dataset. This process took much longer than I expected, partly from learning on the job, but also from the many design decisions we had to make for the individual features. It was akin to gathering hundreds of ingredients for a very complex meal and trying to be intentional about the selection and quality for each one. While the data curation took time, I enjoyed the questioning aspect of the process, being critical about these key decisions.

After data curation, I worked on building models with our new, refined dataset. As a newcomer to machine learning models, my learning curve was steep. It was often unclear what changes to the modeling would translate to better performance; I realized that I could spend many more months training these models with only minimal gains in performance.

Figure 1. The Pythion web application. The screenshot below shows the search interface for procedures—either finding all scheduled procedures within a time range or looking up a specific patient. The screenshot on the next page shows a single procedure with risk scores for each of the modeled outcomes.



This balance between performance and training time became an important concept for me. After I had completed the modeling work, I designed and built a web application as an interface for using the models (Figure 1). A user would be able to see upcoming surgical procedures, each with predicted risk scores for our 12 categories of complications and 60-day mortality. I learned that these risk scores were not the same as probabilities; however, it was often easy to conflate the two. We discussed many options for better interpretation of the risk scores, eventually settling on a percentile-based autocalibration method.

By reporting the percentile of the risk score, we would be able to provide more context to the number without having to determine thresholds manually. After working on several DIHI machine learning projects, I began to see the similarities in the work-flow between projects, thinking about how we could streamline the process. With the help of Michael Gao, I built Slide, a tool that would encapsulate the model training process.

My goal was to make it easier for our teams to focus on data itself and the model training settings, and not have to repeat many of the same repetitive steps involved in creating models. Our RFA 2019 projects ended up using Slide broadly and I hope it can be a useful part of our modeling workflow in the future, especially as we move to a more containerized deployment of models.

I am looking forward to seeing the next steps in the Pythion project as we transition toward clinical implementation and evaluation. Now, as a first-year medical student, it has been truly exciting to start seeing the clinical concepts and paradigms underlying my work at DIHI. I hope to apply the lessons I have learned from clinical machine learning models toward solving unmet clinical needs and improving patient care.

DIHI PERSPECTIVE

HealthGuard: Machine Learning for Goals of Care Conversations

Michael Gao

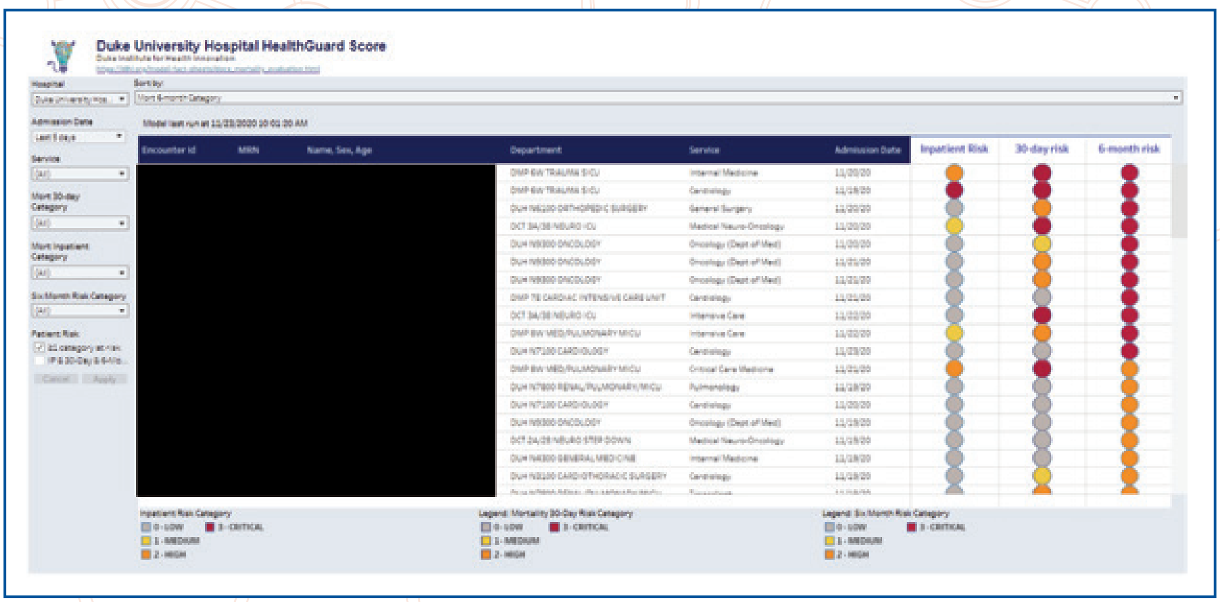
It is an inevitable fact that some of the critically ill patients who come to the Duke University Health System (DUHS) to seek care will die within the hospital. Studies have shown that most Americans would rather die at home than in the hospital, and recent studies have demonstrated a remarkable trend reflecting these preferences. A study published in late 2019 showed that in 2003, 39.7% of deaths in America took place in the hospital; however, in 2017 only 29.8% of deaths took place in the hospital. This was the first time in nearly a century that this percentage was less than that of deaths taking place at home[1].

Although this trend seems promising, one area where there is room for improvement is having goals of care discussions with patients. After all, without eliciting a patient's preferences, it can be difficult to provide the most appropriate care. However, goals of care discussions are hard to have and can happen too late in a patient's disease course.

There are several reasons why having goals of care discussions are important to patients, providers, and health systems. It goes without saying that patients can often benefit from these discussions. Readmission rates and aggressive end of life care are often reduced after goals of care discussions and/or advanced care planning are considered[2, 3].

Despite their importance, goals of care and advanced care planning are often overlooked when taking care of critically ill patients who arrive at the hospital due to an acute episode. At the Duke Institute for Health Innovation (DIHI), we built the HealthGuard system to address this gap. Powering HealthGuard is a machine learning model which utilizes a patient's medical history, laboratory values, vital signs, and other structured data elements within the electronic health record in order to assess a patient's risk of mortality and suitability for advanced care planning and/or goals of care discussions.

Figure 1: HealthGuard patient list of inpatient mortality risk level per patient, sortable by demographic, department, service, and risk level.



The model was trained on hundreds of thousands of patient records and can predict the risk of a patient dying within an inpatient stay, 30 days after the admission, and 6 months after the admission with remarkable accuracy. When the model flags a patient who is at risk for death within 6 months, it is right 50% of the time and captures 50% of all deaths within 6 months.

However, having a model is not enough. At DIHI, we are focused on making sure that these tools are actionable. When the model has identified a patient who may benefit from goals of care planning, it sends a notification to a centralized team which then forwards this alert with contextual information to the appropriate provider. In addition, a centralized dashboard updates every hour with new patients who are admitted to the hospital.

In the early days of this project, we have already seen a more than 30% increase in ACP note filings for patients for whom the alert was triggered. We have refined the workflow in collaboration with Performance Services, DHTS, and our clinical partners, and we continue to improve the usability and adoption of the tool. This has required collaboration on many fronts, including the technology infrastructure, language used in the notifications, and user interface. After feedback from our users, we are expanding the tool to include continuous monitoring of a patient's risk as they progress through their stay at Duke as well as tools to predict overall length of stay.

We hope that as this technology matures, patients who come to Duke are more likely to have their voices heard and DUHS can continue to provide the best and most adequate care for our patients moving forward.

This technology has now expanded beyond Duke University Hospital and also includes Duke Regional Hospital, where the model suggests patients for an existing palliative care huddle workflow. Learn more in our next issue!

For more information on the model, please visit www.dihi.org/mortality_evaluation

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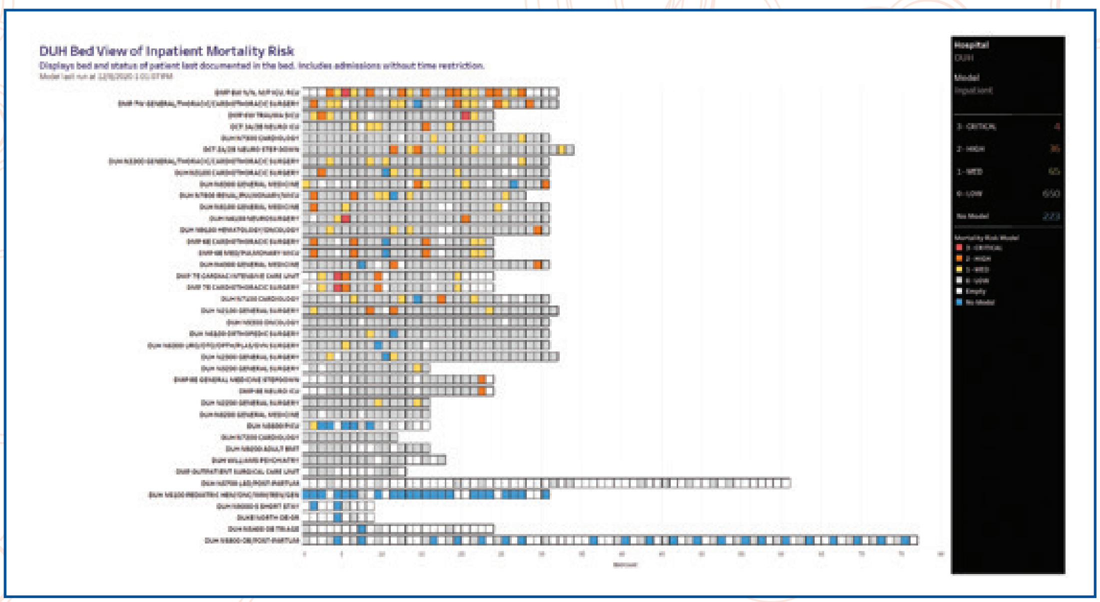
Figure 2: HealthGuard DUH bed view of inpatient mortality risk level per department and bed. Patient demographics pop up when a mouse hovers over one of the squares, which represents a bed.



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TEAM

DIHI Innovation Staff

William Fulkerson, MD
Executive Director for DIHI
Executive VP for Duke University Health System

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

Jamie Daniel
Solutions Architect

Matt Gardner
Solutions Architect

Michael Gao, MS
Data Scientist

Bradley Hintze, PhD
Data Scientist

Will Knechtle, MBA, MPH
Innovation Program Manager

Ebony Nash
Program Coordinator

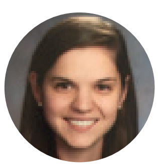
Marshall Nichols, MS
System & Analytics
Manager

Will Ratliff, MBA
Innovation Program
Manager

Mike Revoir
Solutions Architect

Mark Sendak, MD, MPP
Clinical Data Scientist

DIHI Innovation Scholars



Julia Bellantoni

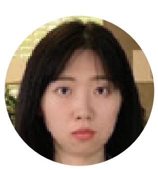
George "Bert" Cortina

Alex Fenn

Zohaib Shaikh

Stephanie Skove

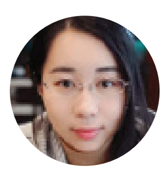
DIHI Data Science Scholars



Mengxuan Cui

Connor Davis

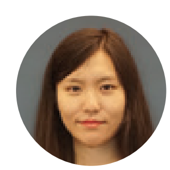
Tong Shen



Ziyuan Shen

Harvey Shi

Sicong Zhao



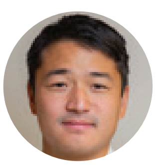
Shujin Zhong

Incoming DIHI Innovation Scholars

Krunal Amin
Krunal is a third-year medical student at Duke and a DIHI scholar working on the "Machine Learning for Early Identification and Management of Pulmonary Embolism" 2020-2021 RFA project. Originally from Burlington, N.C., Krunal completed his undergraduate work at UNC-Chapel Hill as a Morehead-Cain Scholar and remains loyal to his Tar Heels. Prior to medical school, he worked as a business analyst at Deloitte Consulting where he served a wide range of clients across the healthcare industry. Krunal is passionate about finding new ways to deliver higher quality, more compassionate patient care. In his free time, he enjoys exploring Durham's many bike trails and restaurants.

Namita Kansal
Namita is a third-year medical student at Duke and a 2020-2021 DIHI scholar. Her primary project at DIHI is "Development of a Maternal Early Warning System Using Machine Learning." Namita has been proud to be "forever Duke" since 2013 when she first arrived in Durham as an undergraduate. Following graduation in 2017, she completed her MPH at George Washington University with a concentration in maternal and child health. She hopes to pursue a career in OB/GYN and is excited to work at the intersection of machine learning and medicine through DIHI. In her free time, Namita loves bingeing mind-numbing Netflix shows, singing karaoke, and raving about NoVA. Her perfect Sunday morning always begins with a Strawberry Splash smoothie from Durham's finest, Foster's Market.

Akash Patel
Akash is a third-year medical student at Duke who is doing his research year as a DIHI scholar primarily working on the 2020-2021 RFA project "Development and Implementation of a Hospital at Home Program in Wake County." He is from Georgia but has been in North Carolina since his time as a Duke undergraduate. Although he has not finalized his specialty choice, he is considering internal medicine with further sub-specialization, dermatology, or a procedural specialty. He is also interested in data science, healthcare innovation, and hospital finances. After a long week in the hospital, you can probably catch him drinking a cookies and cream milkshake at The Parlour.



Leland Pung
Leland is a third-year medical student at Duke and a DIHI scholar primarily working on the 2020-2021 RFA project "E-Consult Platform for NAFLD." Leland plans to apply to Interventional Radiology residency programs in the not-so-distant future. Before joining DIHI and starting medical school, Leland obtained his master's degree in translational medicine from the University of California, Berkeley and worked as an engineer for 3 years. He enjoys coffee and milk foam cap tea from MILKLAB.

Samantha Wong
Samantha is a third-year medical student at Duke and a DIHI scholar working on the 2019-2020 RFA project "Dermatology Clinical Decision Support in Primary Care." As an aspiring family medicine physician, she hopes to continue her work supporting primary care physicians with machine learning to ease their heavy workloads. Prior to attending Duke, Samantha studied microbiology and toxicology at the University of California, Berkeley, where she was able to apply her love of teaching to the areas of biology, MCAT prep courses, computer science, and knitting. In her free time, Samantha enjoys exploring and trying out new Durham restaurants with her friends. An avid tea drinker, she's always down to venture to MILKLAB for their strawberry rose tea.

DIHI Collaborators


Yvonne Acker, RN


Colette Allen, NP


John Anderson, MD


Mary Ann Fuchs, DNP, RN


Jonathan Bae, MD


Raquel Bartz, MD, MMCi


Armando Bedoya, MD, MMCi

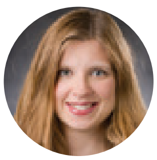

Ashok Bhatta, MSc


Richard Biever

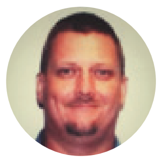

Anne Boyd, RT(R)(N)


Kaitlin Boyle, RN


Kendall Bradley, MD


Danielle Brander, MD


Marion Broome, PhD, RN


Tres Brown


Dan Buckland, MD

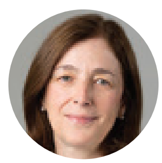

Bill Burton


Larry Carin, PhD


Anisha Chandiramani, MD


Alex Cho, MD, MBA


Chad Cook, PT, PhD, MBA


Kathy Cooney, MD


Connor Davis, MS


Susan Dent, MD

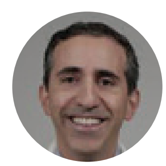

Dinesh Divakaran, PhD, MBA


Jill Engel, DNP


Jeffrey Ferranti, MD


Jon Fjeld, PhD


Katie Galbraith, MBA


Ziad Gellad, MD


Charles Gerardo, MD


Ben Goldstein, PhD


Karen Goldstein, MD


Michael Harrison, MD

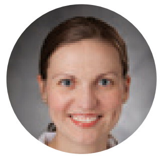

Jeff Hawley


Mitchell Heflin, MD, MHS

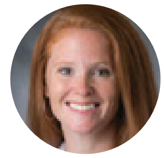
DIHI Collaborators
Continued

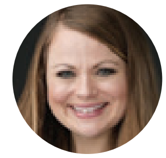

Ricardo Henao, PhD


Adrian Hernandez, MD, MHS


Rachel Hughes, MD


Terry Hyslop, PhD


Kimberly Jackson, MD


Heather Jacobson, SLP


Aubrey Jolly Graham, MD


Schuyler Jones, MD


Neel Kapadia, MD


Jason Katz, MD, MHS


Joe Kelly


Kelly Kester, MSN


Michel Khouri, MD


Elisabeth Kidd, PA


Allan Kirk, MD, PhD


Mary Klotman, MD

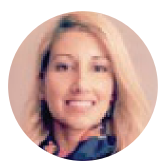

Charley Kneifel, PhD


Karan Kumar, MD, MS


Walter Kwiatek


Sandhya Lagoo-Deenadayalan, MD, PhD


Andy Lamb


Shamayla Lando


Tally Lassiter, MD, MHA


Jennifer Li, MD, MHS


Mary Lindsay, MSN

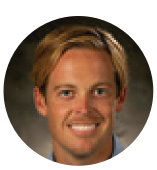

Bruce Lobaugh, PhD

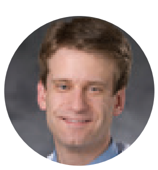

Darin London

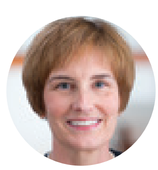

Chad Mather, MD, MBA


Joseph Mathew, MD, MBA, MHSc


Andrew McCrary, MD, MS


Coleman Mill, MA, CCRP


Clay Musser, MD

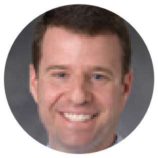

Kristin Newby, MD, MHS

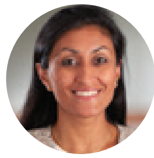

Paul Newman, MHA

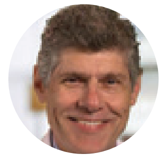

Cara O'Brien, MD


Kevin Oeffinger, MD


Karen Osborne, BSN, RN

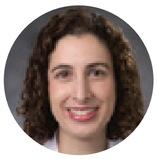

Tom Owens, MD


Neha Pagidipati, MD, MPH


Ted Pappas, MD


Chet Patel, MD

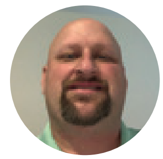

Manesh Patel, MD


Juliessa Pavon, MD


Michael Pencina, PhD


Donna Phinney, RN


Mihai Podgoreanu, MD


Jeremy Poling


Eric Poon, MD

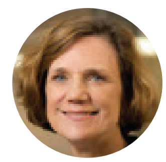

Robin Rasor, MS


Emily Reinke, PhD


Joseph Rogers, MD


John Rollman

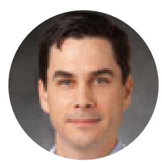

Matthew Roman, MHA

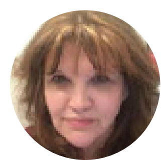

Moira Rynn, MD


John Sampson, MD, PhD, MBA


Dev Sangvai, MD, MBA

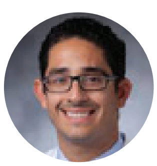

Sharlini Sankaran, PhD


Jacob Schroder, MD


Teri-Lynne Sennett


Noppon Pooh Setji, MD


Kevin Shah, MD


Mohammad Shahsahebi, MD, MBA


Richard Shannon, MD

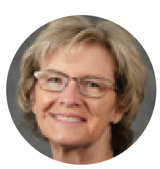

Shilpa Shelton, MHA


Tong Shen, MS


Xiling Shen, PhD


John Shepherd


Harvey Shi


Gail Shulby, RN, MA


Shijing Si, PhD

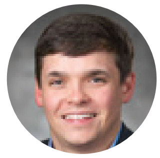

Becky Smith, MD


Denise Snyder, MS, RD

DIHI Collaborators
Continued


Sean Sondej, MHA


Michael Spiritos, MD


Dustin Tart, RN

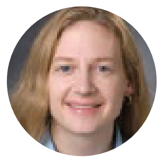

James Tcheng, MD


B. Jason Theiling, MD


Carey Unger, MHA

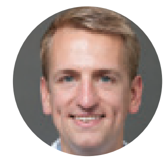

Sreekanth Vemulapalli, MD


Anthony Viera, MD, MPH


Emily Vinson, MD


William Walker, PhD


Wendy Webster, MBA


Zach Wegermann, MD

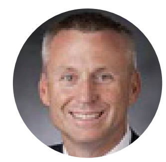

Heidi White, MD


Billy Willis, PhD


Daniel Witt, MIDS


Jocelyn Wittstein, MD


Jedrek Wosik, MD


David Zaas, MD, MBA


Shujin Zhong


Leah Zullig, PhD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You're why.
Wear a mask to keep those near you safe.

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