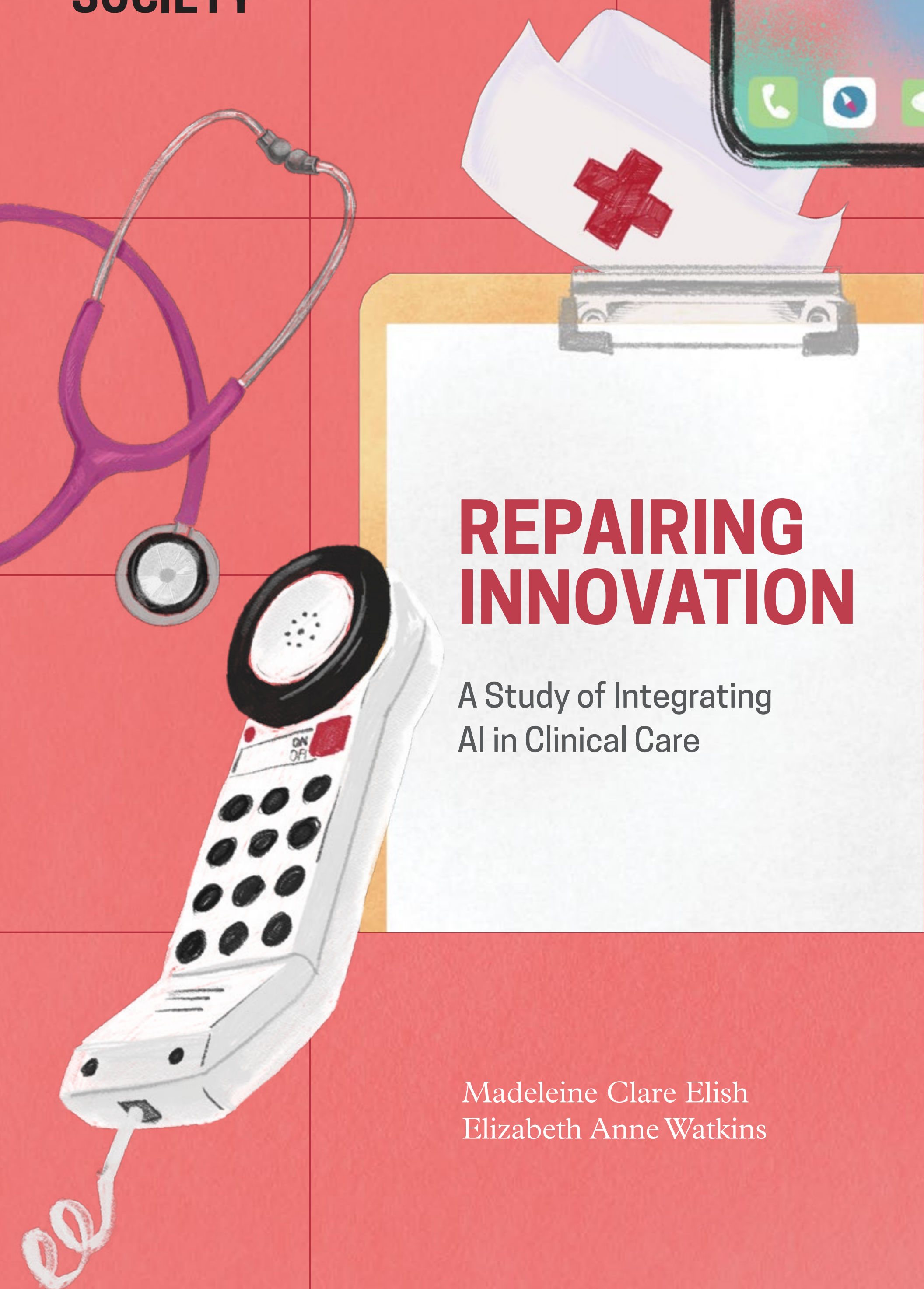
DATA & SOCIETY



REPAIRING INNOVATION

A Study of Integrating AI in Clinical Care

Madeleine Clare Elish
Elizabeth Anne Watkins

September 2020

EXECUTIVE SUMMARY

Over the past two years, a multi-disciplinary team of clinicians and technologists associated with Duke University and Duke Health system have developed and implemented Sepsis Watch, a sociotechnical system combining an artificial intelligence (AI) deep learning model with new hospital protocols to raise the quality of sepsis treatment. Sepsis is a widespread and deadly condition that can develop from any infection and is one of the most common causes of death in hospitals. And while sepsis is treatable, it is notoriously difficult to diagnose consistently. This makes sepsis a prime candidate for AI-based interventions, where new approaches to patient data might raise levels of detection, treatment, and, ultimately, patient outcomes in the form of fewer deaths.

As an application of AI, the deep learning model tends to eclipse the other parts of the system; in practice, Sepsis Watch is constituted by a complex combination of human labor and expertise, as well as technical and institutional infrastructures. This report brings into focus the critical role of human labor and organizational context in developing an effective clinical intervention by framing Sepsis Watch as a complex sociotechnical system, not just a machine learning model. This approach helps highlight two important but understudied aspects of AI development:

First, examining the process of developing and integrating Sepsis Watch demonstrates that in order to be successful, AI interventions must always be thought of as sociotechnical systems, in which social context, relationships, and power dynamics are central, not an afterthought. AI and machine learning technologies are often looked to as being the key to a solution. However, all too often potential solutions remain just that—*potential* solutions, which may work in theory, given pre-set conditions. Rarely are these solutions tested, verified, or even used "in the wild." For this reason, we need fewer studies proposing how AI technologies *could* be used to address existing problems in the abstract, and more studies exploring *how and in what ways* could AI technologies *be integrated into existing*

social processes such that they actually address those problems. The case study of Sepsis Watch is one example of how technology is integrated into a specific context and what it means to address a problem through a sociotechnical intervention.

Second, our analysis of the new and necessary forms of human labor in Sepsis Watch demonstrates the importance of understanding innovation and expertise as occurring throughout the implementation process, not just in the research or design phase. Our research demonstrates that when technology-driven innovation is disruptive, it will always require corresponding *repair work* to complete the process of effective innovation. If the introduction of new technologies such as AI are beneficial because they are disruptive—in that they create new pathways to achieve a goal—this disruption also causes forms of breakage, upsetting existing power hierarchies or rerouting information flows that must be *repaired* in order for the intervention to work effectively in a particular context. Repair work can take many forms, from emotional labor to expert justifications, and involves the labor of integrating a new technology into an existing professional context.

Repair work is not about *recovering* a status quo but rather about creating a *new* set of practices and possibilities. This kind of repair work is necessary, consistently undervalued, and often rendered invisible. Recognizing repair work shifts our focus from those who initiate a project to those whose work and skill is required to make the project work out in the world. If only the work of initiation and theoretical construction, typically elite and masculine forms of work, are valued when it comes to the future of AI and society, then so much of the actual day-to-day work that is required to make AI function in the world is rendered invisible and undervalued, further contributing to conditions of social inequality. The surfacing of repair work labor is a means to think productively about the future of work and how the dignity of all humans who work with the AI systems of the future can be enhanced, rather than diminished.

CONTENTS

INTRODUCTION

Tucked away on the seventh floor of the hospital in the Cardiac Intensive Care Unit, Jennifer,[1] who is a specialized Rapid Response Team (RRT) nurse, sits in front of a computer at her work station. There is also an iPad on the desk beside her, a telephone, and a piece of scrap paper with neatly organized hand-written notes. The back wall of the workstation is lined with thick, plastic binders full of printed protocols and unit information. Pinned in easy reach are several laminated pieces of paper displaying useful phone numbers and recent changes to common protocols. As an RRT nurse, Jennifer provides care during acute health crises across all units of the hospital, and now her shift responsibilities also include monitoring a new artificial intelligence (AI) application on an iPad.[2] The application is part of Sepsis Watch, a system that incorporates deep learning in order to improve the care of patients who develop sepsis.[3]

Unless you know someone who has had sepsis, you may have never heard of it. However, sepsis is widespread and deadly. When someone develops sepsis, their immune system has kicked into overdrive while fighting an infection and begun attacking different parts of the body—in addition to any infection. As the body attacks itself, this can lead to organ failure and death if left unchecked. Sepsis can develop from any infection—from a post-surgical incision, to a kidney infection, to postpartum recovery.

1 Participation in clinical research interviews and observations was anonymized to facilitate open conversation and minimize potential negative professional risks. Quotes or perspectives attributed to only a first name are pseudonyms and can be thought of as characters that are amalgamations of individuals to prevent re-identification of specific individuals while still reflecting the views and backgrounds of clinicians working at the hospital. The clinician and technical leads on the project are available publicly and their full names are used with permission in this report.

2 Artificial intelligence refers to a constellation of technologies that allow a system to display "intelligent" behavior. Much of what is called artificial intelligence today refers to complex machine learning, especially a type of machine learning called "deep learning," that involves the processing of huge of amounts of data in order to achieve a goal specified by designers but through a method that designers do not pre-specify.

3 Claire Maiers, "Analytics in action: users and predictive data in the neonatal intensive care unit," *Information, Communication & Society* 20, no. 6 (2017): 915–929.

Sepsis is treatable, and the earlier it is detected, the more likely a patient will survive. However, sepsis is notoriously difficult to diagnose in the early stages, when treatment is most effective. The symptoms of sepsis are shared with many other illnesses, including the flu, and include a high fever, elevated breathing, and an elevated heart rate. Moreover, there is no one standard way to diagnose the condition. Instead, many clinicians simply learn to develop a "gut instinct" for who is likely to develop sepsis.

Given these diagnostic challenges, machine learning researchers have proposed using sepsis as a prime case for introducing predictive models for health care. Machine learning, and in particular, deep learning, is seen by researchers—both clinical and technical—as a means to augment a human doctor's capacity to detect disease in ways that are more refined than existing clinical decision aids. Already, several leading machine learning research labs have undertaken projects to build models that could help predict when individuals will develop sepsis.[4] However, these projects remain largely in the research phase. That is, while the models may be extremely sophisticated and robust, they do not account for the intricacies of integration into the clinical setting.

In contrast, a small innovation team embedded within Duke University and Duke Health system has not only developed a model that predicts patients at high risk for developing sepsis, but has piloted and integrated the project into routine clinical care. This system is Sepsis Watch, and as a kind of clinical support decision system its goal is to improve and support the diagnosis and care of sepsis in the Duke Emergency Department. A core component of Sepsis Watch is a deep learning model that predicts the risk of a patient developing sepsis. In news coverage, marketing, and even conversations about the project, the deep learning model—as an application of AI—frequently eclipses the other parts of

4 The Machine Learning for Health conference represents a growing community working on these issues: https://www.mlforhc.org/

the system;[5] in practice, Sepsis Watch is constituted by a complex combination of human labor and expertise, as well as technical and institutional infrastructures. By framing Sepsis Watch as a complex sociotechnical system, not just a machine learning model, this report brings into focus the critical role of human labor and organizational context in developing an effective clinical intervention.

This report is based on research conducted in collaboration with and alongside the Duke team, and applies a sociological lens to analyzing how Sepsis Watch, as a sociotechnical system, has become an effective clinical intervention. The concept of the sociotechnical is key to our analysis. This term is used to recognize the interconnected and inextricable nature of humans and technical objects, and to emphasize, in the words of scholars David MacKenzie and Judy Wajcman that "it is mistaken to think of technology and society as separate spheres influencing each other: technology and society are mutually constitutive."[6]

A snapshot of the tool in use can help bring into focus the complex interactions between humans, data, and AI: when a patient arrives at Duke University Hospital and is admitted to the Emergency Department (ED), her personal electronic health record (EHR) data is run through the Sepsis Watch system. If the model predicts that she is at high risk of developing sepsis, her patient information is displayed as a "patient card" on the Sepsis Watch iPad application. An RRT nurse, who is responsible for monitoring the Sepsis Watch application, regularly checks it to review patient cards. If a patient is predicted to be septic or at high risk, the nurse calls the ED physician responsible for the patient's care, and conveys the risk category to the ED physician over the telephone. If the ED physician agrees the patient requires treatment for sepsis, the patient is further tracked on the iPad application by the nurse until the recommended treatment for sepsis is completed by the ER clinicians. It is this sociotechnical

5 For example, an emblematic headline about the project announced, "Hospital to roll out AI system for sepsis.": Harrison Cook, "Hospital to roll out AI system for sepsis," *Becker's Health care* 2018. https://www.beckershospitalreview.com/quality/duke-university-hospital-to-roll-out-ai-system-for-sepsis.html.

6 Donald MacKenzie and Judy Wajcman, *The social shaping of technology* (Open university press, 1999) 23.

ensemble of human actors, technical infrastructure, and expert interactions that ultimately improves patient care.

As a case study in AI innovation, Sepsis Watch has many important lessons. Most centrally, the process of developing and integrating Sepsis Watch demonstrates that in order to be successful, AI interventions must always be thought of as sociotechnical systems, in which social context, relationships, and power dynamics are central, not irrelevant or an afterthought. AI and machine learning technologies are often held up as the answer to the world's most pressing problems, in the pages of media as well as multi-million-dollar contests and grants. However, all too often, potential solutions remain just that—*potential* solutions, which may work in theory, given pre-set conditions. Rarely are these solutions tested, verified, or even used "in the wild." For this reason, we need fewer studies proposing how AI technologies *could* be used to address existing problems in the abstract, and more studies exploring *how and in what ways* could AI technologies *be integrated into existing social processes* such that they actually address those problems. The case study of Sepsis Watch is one example of how technology is integrated into a specific context and what it means to address a problem through a sociotechnical intervention.

A related lesson we draw from our research on Sepsis Watch is that when technology-driven innovation is disruptive, it will always require corresponding *repair work* to complete the process of effective innovation. If the introductions of new technologies like AI are beneficial because they are disruptive in the sense of creating new pathways to achieve a goal, this disruption is also a kind of breakage that must be *repaired* in order for the intervention to work effectively in a particular context. The breakages do not occur because the technologies are being used incorrectly or because the technologies themselves are broken. Rather, these breakages are a result of the system's design, itself. The breakages to existing social and institutional norms and processes may have some benefits, but in many other instances, require what we describe as *repair work*. Repair work can take many forms, from emotional labor to expert justifications, and involves the labor of integrating a new technology into an existing professional context. Repair work is not about *recovering* a status quo but rather about creating a *new* set of practices and possibilities. This kind of repair work is necessary, consistently undervalued, and often rendered invisible.

In this report, we examine how Sepsis Watch was integrated into the clinical context through the repair work of a particular set of clinicians, a group of specialized RRT nurses. Their consequential and constituent labor was necessary in order to integrate an AI technology into existing workflows, and examining this labor is important if we want to understand how to develop effective AI-driven solutions. The surfacing of this labor is also a means to expand our understanding of what constitutes innovation—who does it, what it looks like, and where it happens. The work of repair also requires creativity, skill, and ingenuity—and it should be valued as such. If only the work of initiation and theoretical construction, typically elite and masculine forms of work, are valued when it comes to the future of AI and society, then so much of the actual day-to-day work that is required to make AI function in the world is rendered invisible and undervalued, further contributing to conditions of social inequality.[7] The surfacing of this kind of innovation and the labor entailed is a means to think productively about the future of work and how the dignity of all humans who work with the AI systems of the future can be enhanced, rather than diminished.

7 Lily Irani. "Difference and dependence among digital workers: The case of Amazon mechanical turk." *South Atlantic Quarterly*, 114, 1 (2015): 225–234. Hamid R. Ekbia and Bonnie A. Nardi. *Heteromation, and Other stories of computing and capitalism* (Cambridge, MA: MIT Press, 2017); Mary L. Gray and Siddharth Suri, *Ghost work: How to stop Silicon Valley from building a new global underclass* (San Francisco, CA: HMH Books, 2019).

Define: sociotechnical

The term sociotechnical is an adjective that indicates the inextricable relationship between “social” and “technical” components of a system—emphasizing that technology shapes society, at the same time society shapes technology. The term first emerged during post-World War II studies of UK mining practices, when researchers found that workers were responding to the integration of new tools by creating new, unforeseen workflows. To consider a system sociotechnical is to acknowledge that its function emerges from the interplay of its theoretical design and its actual use.

Historian of science Thomas P. Hughes used electrical power production as a classic example of a sociotechnical system. This system has many technical components: a power plant, electrical lines, sockets, and switches. However, these objects alone do not explain how the system of electrical production works, how it accomplishes its designated purpose. The technical infrastructure of the system is bound up with a social infrastructure. It includes organizations of people, like the utility company and their suppliers, as well as the engineers and salespeople who work for the company. The production of electricity is shaped by social arrangements like state tax regulations and scientific standards for measuring power. For any sociotechnical system, therefore, there is work involved in identifying which components (both technical and social) are relevant to its function.

In the case of Sepsis Watch, the use of the machine learning tool cannot be considered apart from the people and institutions who interact with it, as well as the beliefs, contexts, and power hierarchies that shaped its development and use. As we clarify in this report, this means that the Sepsis Watch nurses and their emergent workflows are just as much a part of the system as the machine learning model and iPad application.

Define: artificial intelligence

The phrase artificial intelligence, or AI, has been used for decades to refer to a constellation of technologies that allow a computer system to display “intelligent” behavior. However, what constitutes “intelligence” does not have a clear answer, and even technical definitions of artificial intelligence vary. A commission of experts convened by the European Union proposed this overarching definition in 2019: “an Artificial intelligence (AI) refers to systems that display intelligent behaviour by analysing their environment and taking actions—with some degree of autonomy—to achieve specific goals.”

It can be useful to think of artificial intelligence not as an inherent capacity of a technology, but as a socially-constructed concept that is as much about technical capability as it is about an exciting marketing term. In previous research we’ve found that the prevalence of the term has led to both benefits and harms: when something is described as “AI,” everyone has a clear picture in their mind; the problem is that everyone’s picture is different.

In recent years, AI has typically been used to describe machine learning, especially a type of machine learning called “deep learning,” that involves the processing of huge of amounts of data in order to achieve a goal specified by designers but through a process that designers do not pre-specify. Computer scientist Tom M. Mitchell gives a classic definition of when a machine “learns”: “A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E.” In other words, machine learning programs are those that change and improve their performance over time.

Throughout this report, we use “AI” in both its technical dimensions and social connotations. A significant part of the Sepsis Watch system is a deep learning model that analyzed patient data to make risk predictions, and this model changes and refines these predictions over time. It is important to understand this technical dimension of the Sepsis Watch AI, and there is further technical detail in footnotes throughout the report. However, it is also crucial to consider how the description of Sepsis Watch as an AI intervention into health care affected the support and interpretation of the program as a whole.

Background: a Problem in Search of a Solution

The problem: Sepsis

Sepsis is a leading cause of hospital deaths, and rapid diagnosis is a major challenge.[8] The World Health Organization recognizes sepsis as a major cause of preventable disease and death globally, particularly impacting low- and middle-income countries.[9] In the United States, sepsis is the leading cause of death for patients who die in a hospital.[10] Over a million people a year in the United States develop sepsis, with Black patients experiencing higher rates of severe sepsis than white patients.[11] While those who are immunocompromised, like the very young, the very old, or those with cancer, are at greater risk to develop sepsis, anyone of any age or health status can develop sepsis and go into septic shock, an advanced state of sepsis in which the body begins to shut down and which is likely to result in death.

One of the most well-known research and advocacy foundations focused on sepsis prevention and treatment, the Rory Staunton Foundation, was founded by two parents who lost a child to sepsis. Their young and otherwise healthy son, Rory, came home with seemingly minor cuts from a fall at school.[12] Within days, Rory was dead. Rory's story parallels the stories of many others who developed sepsis and died: a relatively minor infection rapidly spirals and is

---

8 Roni Caryn Rabin, "Could It Be Sepsis? C.D.C. Wants More People to Ask," *The New York Times*, 2016.

9 World Health Organization, "Improving the prevention, diagnosis and clinical management of sepsis," April 13, 2017, http://apps.who.int/gb/ebwha/pdf_files/WHA70/A70_13-en.pdf.

10 Chanu Rhee, Raymund Dantes, Lauren Epstein, David J. Murphy, Christopher W. Seymour, Theodore J. Iwashyna, Sameer S. Kadri et al. "Incidence and trends of sepsis in US hospitals using clinical vs claims data, 2009-2014." *Jama* 318, no. 13 (2017): 1241-1249.

11 Amber E. Barnato, Sherri L Alexander, Walter T Linde-Zwirble, and Derek C Angus, "Racial variation in the incidence, care, and outcomes of severe sepsis: analysis of population, patient, and hospital characteristics," *American Journal of Respiratory and Critical Care Medicine* 177, 3(2008):279-284, doi:10.1164/rccm.200703-480OC; Justin Xavier Moore, John P. Donnelly, Russell Griffin, Monika M. Safford, George Howard, John Baddley, and Henry E. Wang, "Black-white racial disparities in sepsis: a prospective analysis of the Reasons for Geographic And Racial Differences in Stroke (REGARDS) cohort," *Critical care* 19, 1 (2015): 279, https://doi.org/10.1186/s13054-015-0992-8.

12 Orlaith Staunton, "The Rory Staunton Foundation for Sepsis Prevention," *Huffington Post*, November 15, 2016.

ignored or misdiagnosed. By the time a diagnosis of sepsis has been reached, septic shock has occurred and it is too late. Compounding the tragedy, sepsis is treatable if diagnosed in time. Most health care professionals and clinicians agree: the way to decrease the number of people who die from sepsis is primarily by improving *diagnosis,* rather than treatment.[13]

“Sepsis is always a priority,” explained Elena, a physician who had been involved in the development of Sepsis Watch. “From the moral and ethical [perspective], sepsis is just really bad. Getting better at treating it, that saves people’s lives. And there’s also the brick and mortar bottom line. Caring for patients who get septic is very costly.” As this physician articulated, the motivations to improve care for sepsis are rooted in both human and financial costs.

While sepsis is universally recognized as a major health concern, there is no one standard way to diagnose it. “Patients don’t come in and say, ‘I feel septic’” Priya, another ED physician pointed out to us, “More often, it’s like, ‘I just don’t feel good.’” In practice, it is the kind of illness doctors and nurses just learn to develop “a gut instinct” about.[14] This is in part because there are no definitive lab tests. A blood culture can help identify the pathogen causing sepsis, but this test can take over 24 hours to produce useful information that clinicians can use to direct treatment. By the time a result is back, it may be too late.

Not only is there no one standard method to diagnose sepsis, there is also no one standard definition of what sepsis *is*. Definitions of sepsis differ among organizations and standards bodies. There may be different definitions for types of patients. One expert review concluded that “it is an elusive task to generate a single

13 World Health Organization, “Improving the prevention, diagnosis and clinical management of sepsis,” World Health Organization Report by the Secretariat, April 2017. See also: Jonathan Cohen, Jean-Louis Vincent, Neill KJ Adhikari, Flavia R. Machado, Derek C. Angus, Thierry Calandra, Katia Jaton et al., “Sepsis: a roadmap for future research,” *The Lancet infectious diseases* 15, 5 (2015): 581–614, Doi:10.1016/S1473-3099(15)70112-X .

14 Maiers. “Analytics in action.”

all-encompassing definition."[15] Even when sepsis experts from across the country were asked to review patient cases, raters often failed to agree on a sepsis diagnosis.[16]

While sepsis is a difficult illness to diagnose, once a diagnosis has been reached, there are relatively standardized protocols for treatment. These protocols, known as "bundles," include giving specific types of antibiotics, pushing intravenous fluids, and repeating particular lab tests. In the United States, the Centers for Medicare and Medicaid Services (CMS) have developed a specific evidence-based protocol for treating sepsis, the SEP-1 bundle. CMS, the federal government program that oversees Medicare and Medicaid, is the largest purchaser of health care in the United States, and it uses its purchasing power to require hospitals to report data publicly about performance measures. From this position, CMS has become a primary standards-setting body for evidence-based health care.[17] In the case of treating sepsis, compliance with the SEP-1 bundle protocol has been shown to improve patient outcomes in many hospitals. [18]However, treating sepsis according to these evidence-based guidelines and improving patient outcomes remains a challenge. Hospital

15 Derek C. Angus, Christopher W. Seymour, Craig M. Coopersmith, Clifford Deutschman, Michael Klompas, Mitchell M. Levy, Greg S. Martin, Tiffany M. Osborn, Chanu Rhee, and R. Scott Watson, "A framework for the development and interpretation of different sepsis definitions and clinical criteria," *Critical care medicine* 44, 3 (2016): e113.

16 Laura Evans, "A Closer Look at Sepsis-Associated Mortality," *JAMA* network open 2, 2 (2019): e187565-e187565.

17 One of the mandates of the Centers is to assess the quality of health care provided at over 4,000 health care systems in the United States and post the assessments publicly. Hospitals are required to demonstrate compliance with the standards of care mandated by the CMS in order to receive reimbursement for Medicare and Medicaid patients.

18 Chanu Rhee, Michael Filbin, Anthony F. Massaro, Amy Bulger, Donna McEachern, Kathleen A. Tobin, Barrett Kitch, et al., "Compliance with the national SEP-1 quality measure and association with sepsis outcomes: a multicenter retrospective cohort study," *Critical care medicine* 46, 10 (2018): 1585; Christopher W. Seymour, Foster Gesten, Hallie C. Prescott, Marcus E. Friedrich, Theodore J. Iwashyna, Gary S. Phillips, Stanley Lemeshow, Tiffany Osborn, Kathleen M. Terry, and Mitchell M. Levy, "Time to treatment and mortality during mandated emergency care for sepsis," *New England Journal of Medicine* 376, 23 (2017): 2235-2244.

systems often pilot new programs and protocols in an effort to improve patient care and demonstrate their compliance with the CMS protocol guidelines, but results have been mixed.[19]

At Duke Health, like many other US hospitals, sepsis care is a concern for hospital management. Since the 2010s, the hospital system had been trying to improve patient outcomes—and the public metrics of care—through targeted interventions. These included best practice advisories and the implementation of a pop-up window program that would alert clinicians to high-risk patients when they were working in a patient's electronic health record (EHR) on a bedside computer. The interventions above were assessed by the clinicians involved in the project to have had limited results.[20] One of the major disappointments of the program had been how quickly nurses learned to ignore the pop-up windows by clicking them closed. The clinicians understood this as a form of "alarm fatigue," a common phenomenon especially in health care settings, where the sheer volume of alerts and notifications, as well as the high rate of false alarms, desensitizes a practitioner, limiting the effectiveness of the alerts.

The intervention: Sepsis Watch

In 2017, two of the Duke physicians who had been involved in the earlier sepsis improvement projects submitted a proposal to the Duke Institute for Health Innovation to work on a collaborative project, dubbed Sepsis Watch, to develop a machine learning-driven intervention. The institute, known as DIHI (pronounced dee-hi), bridges Duke University and Duke Health systems, and

19 Norman Lance Downing, Joshua Rolnick, Sarah F. Poole, Evan Hall, Alexander J. Wessels, Paul Heidenreich, and Lisa Shieh, "Electronic health record-based clinical decision support alert for severe sepsis: a randomised evaluation," *BMJ quality & safety* 28, 9 (2019): 762-768; Armando D. Bedoya, Meredith E. Clement, Matthew Phelan, Rebecca C. Steorts, Cara O'Brien, and Benjamin A. Goldstein. "Minimal impact of implemented early warning score and best practice alert for patient deterioration," *Critical care medicine* 47, 1 (2019): 49.

20 Armando D. Bedoya, Meredith E. Clement, Matthew Phelan, Rebecca C. Steorts, Cara O'Brien, and Benjamin A. Goldstein, "Minimal impact of implemented early warning score and best practice alert for patient deterioration," *Critical care medicine* 47, 1 (2019): 49.

its mission is to create “innovative solutions” in health care.[21] Each DIHI project is developed by an interdisciplinary team (including experts in project management, data science, software development and implementation, and research partners from the department of statistics, and information technology) in addition to hospital front line staff, such as nurses and physicians, across multiple specialties.

The proposed machine learning project, like the previous pop-up advisory project, focused on the care of septic patients in the Emergency Department (ED). The ED had been identified by internal studies as a department in the hospital that particularly needed improvement.[22] Initially, the clinical leads articulated three main priorities: They wanted to center the intervention not only on improved diagnosis but also on following up on sepsis treatment after diagnosis; they also wanted to develop an application that supported, not replaced, diagnosis by physicians; moreover, they wanted to create an intervention that would not trigger the “alarm fatigue” that undermined the previous pop-up intervention.

Once DIHI selected the Sepsis Watch project, a multi-disciplinary team began working on the project. On the DIHI side, the project was led by a physician and public health expert, as well as a small staff of around five people, including a data scientist, a database engineer, and a designer (most of these were early- or mid-career). On the university side, a PhD candidate and academic advisors were also key contributors. On the clinical side, the project was led by two senior level physicians working at the hospital. Two individuals, the first author and an undergraduate at Duke University, joined the project in 2018 to investigate the social and organizational dimensions of the project. In addition to this core team, over a dozen stakeholders in the project were engaged on a weekly or

21 Social Entrepreneurship Accelerator at Duke: Duke Institute for Health Innovation http://www.dukesead.org/global-health--innovation-at-duke.html.

22 Christelle Tan, Kristin Corey, Mark Sendak, Michael Gao, Marshall Nichols, Mike Revoir, Armando Bedoya, Suresh Balu, and Cara O’Brien, “Characterizing Sepsis Encounters Across Community and Quartnerary Hospitals Within an Academic Health System,” Abstract published at Hospital Medicine, March 24–27, 2019. National Harbor, MD. Abstract 188. See also: A.L. Lin, M.P. Sendak, A.D. Bedoya, M. Clement, J. Futoma, M. Nichols, M. Gao, K. Heller, C. O’Brien, “What Is Sepsis: Investigating the Heterogeneity of Patient Populations Captured by Different Sepsis Definitions,” *American Journal of Respiratory and Critical Care Medicine* 2020, 201: A3299, doi:197:A3299.

monthly basis, including management leadership from departments, units, and committees across the hospital, from nursing, the ED, and hospital administration to Duke's IT department. Although demographic data was not collected as part of this research, in broad strokes, the racial and gender diversity of the stakeholders was as follows: the core team was predominantly gendered male, although the larger stakeholder group included as many if not more individuals gendered female. The core team and stakeholders were predominantly white and white-passing, and also included several people of color in leadership positions. The demographics roughly reflect those of the Duke University workforce, in which over half of the workforce identify as women, the average age of a Duke employee is about 45, and nearly 70% identify as white.[23]

The first year of the project involved obtaining and cleaning historical local retrospective data for inpatient admission at Duke University Hospital over the course of 14 months in 2014 and 2015. The data was extracted from patient electronic health records (EHR) that are securely stored in Duke's EHR provider, Epic Systems. To provide a sense of the size and make-up of this data, the hospital is an academic research and urban teaching hospital with over 1,000 beds and over 40,000 inpatient admissions per year, making it one of the 30 largest hospitals in the United States.[24] While Duke does not publicly report data about patient race, the county in which Duke operates, Durham County, is about 54% white, 37% Black or African American, 6% Asian, less than 1% Native American and Pacific Islander combined, and with almost 14% identifying as Hispanic or Latino.[25] In addition to serving the local county, the hospital also attracts patients throughout the region because it is a large and high profile research hospital.

23 These numbers are drawn from the most recent public Duke reporting: https://today.duke.edu/2017/05/who-are-we; https://today.duke.edu/2012/12/dukedemographicsraceethnicity.

24 Laura Dyrda, "100 of the largest hospitals and health systems in America: 2019," *Becker's Hospital Review*, September 12, 2019.

25 US Census, "QuickFacts," 2019, https://www.census.gov/quickfacts/durhamcountynorthcarolina.

As the dataset was cleaned and curated by DIHI staff, a PhD researcher, in collaboration with clinical (physician) leads, statisticians and other DIHI staff, developed a data model to predict the likelihood of a patient to develop sepsis. First, the clinical leads identified the variables they thought should be included, and then a small team of clinical leads and statisticians further refined the variables included as features of the model. The model draws on static variables (patient demographics and pre-admission diagnoses), as well as dynamic variables that will change over the course of a patient's stay (like vital sign measurements, medication administrations, and lab results).[26] The model analyzes this data and produces a risk score for a patient every hour.[27] In total, the model development and evaluation dataset contained over 32 million data points.

Early in the process, the DIHI team had to confront the difficulties of sepsis' lack of an official definition. Usually, machine learning models are developed relative to a concept of a "ground truth," the real phenomenon the model is meant to predict. In the case of sepsis, as one technical lead put it, the "ground truth doesn't exist." To accommodate this, the DIHI team had to come up with their own local definition of sepsis, which would approximate ground truth. The team, led by the clinicians, ultimately decided on a definition of sepsis that encompassed and slightly refined the CMS definition of sepsis.[28] Current definitions of sepsis, as well as the recommended treatment bundles, are imperfect. They represent definitions and guidelines, developed by experts based on scientific evidence and current

26 Racial data is not collected as part of Duke's electronic health data, and neither race nor ethnicity were included as variables in the model.

27 Joseph Futoma, Sanjay Hariharan, and Katherine Heller, "Learning to Detect Sepsis with a Multitask Gaussian Process RNN Classifier," *Proceedings of the 34th International Conference on Machine Learning*, Sydney, Australia, PMLR 70; Joseph Futoma, Sanjay Hariharan, Katherine Heller, Mark Sendak, Nathan Brajer, Meredith Clement, Armando Bedoya, and Cara Obrien, "An Improved Multi-Output Gaussian Process RNN with Real-Time Validation for Early Sepsis Detection," *Proceedings of Machine Learning for Health care* 68 (August 2017): 1–12.

28 Sepsis was defined by the presence of two or more systemic inflammatory response syndrome (SIRS) criteria, a blood culture order, and at least one element of end organ failure. For further discussion of the team's definition and decision, see: Anthony Lin, Mark Sendak, Armando D. Bedoya, Meredith E. Clement, Nathan Brajer, Joseph Futoma, Hayden B. Bosworth, Katherine A. Heller, and Cara L. O'Brien, "Evaluating sepsis definitions for clinical decision support against a definition for epidemiological disease surveillance," *bioRxiv* (2019): 648907, doi: https://doi.org/10.1101/648907.

knowledge of the problem. They also are abstractions and forms of measurement that are not neutral but rather shaped by history and politics.[29] Moreover, as new evidence is gathered, the knowledge of a problem and what constitutes best practices necessarily changes over time.[30]

In basic terms, the model developed the capacity to predict which patients were at high risk to develop sepsis (as defined in the model) by finding correlations between patients who had developed sepsis (defined by the Sepsis Watch clinical team) previously.[31] It's important to note that the model is tuned to correlations, not causation. The model provides no information about *why* a particular patient is at risk for sepsis, only that the patient is at risk. Moreover, the model is uninterpretable, meaning that Sepsis Watch is a "black box" model; there is no practical way for clinicians, or even computer scientists, to understand and explain the logic by which the model generates an output.

Although the deep learning model is uninterpretable, it was thoroughly validated by Duke Health clinicians, statisticians, and the DIHI team. This process of validation, checking that the model's predictions were plausible with respect to the outcomes in reality, included forms of technical computer science model validation on datasets that had been held out for the purpose of testing, as well as physicians systematically looking through patient charts to be sure that the model was providing reasonable predictions.

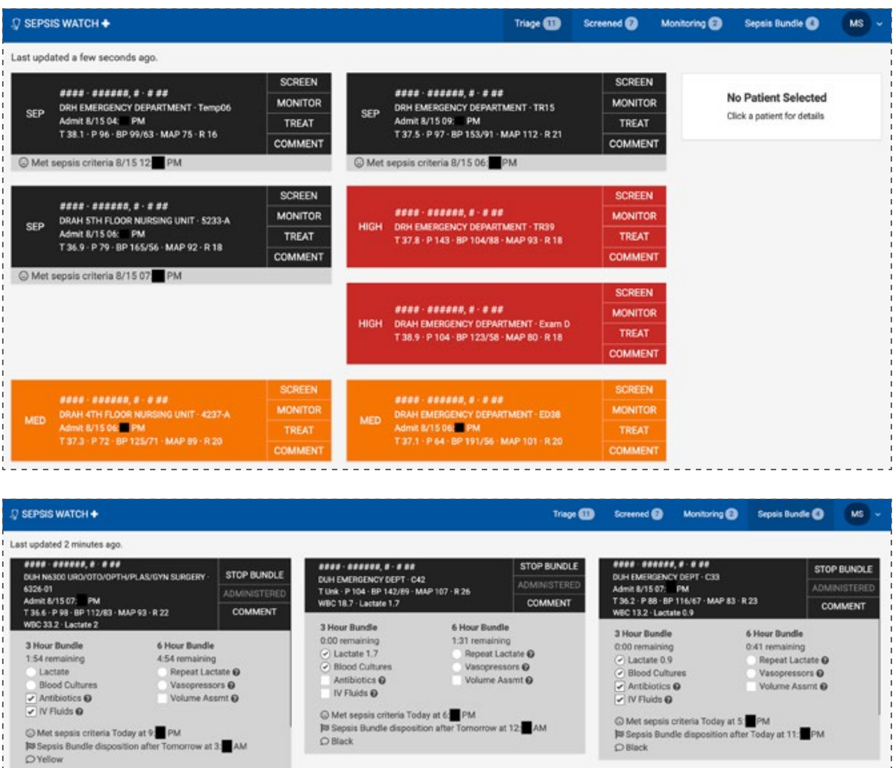
29 Geoffrey C. Bowker and Susan Leigh Star, *Sorting things out: Classification and its consequences.* (Cambridge: MIT Press, 2000); Kathleen H. Pine and Max Liboiron. "The politics of measurement and action," *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, (2015): 3147-3156.

30 A recent example: In 2020, one of the leading researchers on sepsis in US hospitals recommended changes to the standard treatment bundles based on new evidence. Chanu Rhee, Kathleen Chiotos, Sara E. Cosgrove, Emily L. Heil, Sameer S. Kadri, Andre C. Kalil, David N. Gilbert et al., "Infectious Diseases Society of America Position Paper: Recommended Revisions to the National Severe Sepsis and Septic Shock Early Management Bundle (SEP-1) Sepsis Quality Measure," *Clinical Infectious Diseases* (2020), doi:10.1093/cid/ciaa059.

31 The clinical leads of Sepsis Watch decided to use a modified definition of SEP-2 unique to their hospital, including three components: 1) 2 or more SIRS criteria; 2) blood culture order; 3) lab evidence of end organ damage. Documentation of the criteria can be found in Mark Sendak, "Using Constellation to Identify Sepsis," 2019, https://cran.r-project.org/web/packages/constellation/vignettes/identify_sepsis.html, and discussed in Lin et al., 2019.

When in operation in the hospital, Sepsis Watch displays the outputs of the deep learning model (which patients are at high risk for developing sepsis in the ED) through a software application that can be seen through a website or an iPad application (app). The iPad application was designed to be viewed by clinicians and to prioritize ease of use. The design provides an overview of patients at a glance, each patient and their risk represented by color-coded “cards,” with the ability to go further into patient details as needed. Figure 1 provides screenshots of the various “pages” that organize patients: Triage, Screened, Monitoring, and Treatment.

Figures 1:



Sepsis Watch interface, Screenshot. © Duke Institute for Health Innovation 2020.

In addition to developing applications for the nurses, as end users, DIHI developers created two additional tools to monitor Sepsis Watch. These tools, one for web service monitoring and the other for model monitoring, were accessed through dedicated webpages. These tools were designed for the developers or project leads to monitor Sepsis Watch and the complex technical integrations that were required to run it smoothly.

As the technical components of Sepsis Watch took shape, DIHI staff began planning in parallel how the tool would be used and integrated into clinician workflows. Based on the experience of the previous, ineffective, pop-up-based intervention, the lead physicians were committed to avoiding an easily dismissed pop-up window. They were also committed to ensuring nurse "buy-in," a way to describe nursing stakeholder commitment, support, and trust. For these reasons, the team decided to involve a handful of nurses who could represent nurses' perspectives and communicate to the larger team from the very beginning of the workflow design process, and to make nurses a key part of the workflow design, not merely the receivers of a workflow designed by others, such as physicians or computer scientists. The inclusion of nurses as stakeholders to be consulted and listened to was notable given the extent to which organizational hierarchies and power dynamics shape clinician relationships and favor physician over nurse expertise and authority.

Even though Sepsis Watch was being implemented in the ED on ED patients, the clinical leads did not task ED nurses—those nurses who would be directly providing physical care to the patients being screened—with using Sepsis Watch. This decision was based on the limited resources and fast pace of the ED. Instead, the leads proposed that a group of specialized nurses, called the Rapid Response Team (RRT), be given the iPads running the Sepsis Watch app and assigned the duties of monitoring, contextualizing, and communicating Sepsis Watch outputs. This configuration is in contrast to most clinical decision support systems, in which the clinician providing care directly receives the system outputs. Sepsis Watch adds a skilled nurse between the system and the clinician receiving the new information. Nursing and hospital leadership had agreed that there was capacity in the RRT's duties to take part in the Sepsis Watch pilot. These nurses were a category of nurse that reported to one of the clinical leads. Trained as Intensive Care Unit nurses, RRT nurses sit at a workstation on the Cardiac Intensive Care Unit, located on a different floor of the hospital than the ED. RRT nurses traditionally were dispatched to provide additional care during acute health cases across all units of the hospital, with one RRT nurse each shift covering the main hospital building.

A cascade of implications resulted from the decision to develop the nurse workflow in this way. In particular, the workflow design set the terms for the interruptions introduced by the Sepsis Watch model, and consequently, also for the requisite repair work. Because the RRT nurses were not physically located in the ED, the RRT nurses needed to communicate with ED clinicians over the telephone. Recall that real-time communication with a person was a priority given the history of failed pop-up advisories.

After several iterations, the Sepsis Watch team, which included the clinician leads and the DIHI team, arrived at the following Sepsis Watch workflow:[32] When a patient enters the ED, the model analyzes their risk of sepsis and, if the patient is at risk, places them on the Triage page. Each patient is represented by a "card," a color-coded rectangle that can be moved between "pages." If the patient meets sepsis criteria, their "card" is black. If the patient is at high-risk, the card is red, and if the patient is medium-risk, the card is orange.

Following clinical evaluation by a doctor, patients are placed either on the Screened page, if they do not require further evaluation, or are placed on the Monitoring page, if further evaluation is required. If the ED physician chooses to diagnose and treat the patient for sepsis, the patient is moved to the Treatment page and the completion of

32 For a detailed discussion of the design and implementation process see Mark P. Sendak, W. Ratliff, D. Sarro, E. Alderton, J. Futoma, M. Gao, M. Nichols, M. Revoir, F. Yashar, C. Miller, K. Kester, S. Sandhu, K. Corey, N. Brajer, C. Tan, A. Lin, T. Brown, S. Engelbosch, K. Anstrom, M. Elish, K. Heller, R. Donohoe, J. Theiling, E. Poon, S. Balu, A. Bedoya, C. O'Brien, "Sepsis Watch: A Real-World Integration of Deep Learning into Routine Clinical Care" *JMIR Medical Informatics*, 31/12/2019:15182, DOI: 10.2196/15182.

3- and 6-hour sepsis treatment bundle items is tracked. In the case of a disagreement between the ED physician and the Sepsis Watch risk score, as communicated by the RRT nurse, the ED physician ultimately decides the course of treatment.

Each shift, the oncoming RRT nurse was equipped with a tablet loaded with Sepsis Watch, the Sepsis Watch training homepage, and a 2-minute survey for submitting application and workflow feedback on the iPad. The tablet and Sepsis Watch coverage was handed off at the end of each 12-hour nursing shift.

During months of design, development, and testing, the DIHI team worked with different clinician and administration stakeholders to develop relationships and formal modes of communication among different groups.[33] These ranged from standing meetings and the development of nursing education modules to informal pizza parties to build interest and trust in the new technology.

Over the course of two-and-half-years, Sepsis Watch grew from a proposed intervention to a sepsis detection and management technical platform developed to support and improve patient outcomes through increased compliance with recommended treatment guidelines for sepsis. Results from a federally registered clinical trial will be reported in 2021.[34] Anecdotal feedback from hospital managers and clinicians is that Sepsis Watch has dramatically improved the care of patients who are diagnosed with sepsis.

---

33 The modes of stakeholder engagement are detailed in Mark Sendak, Madeleine Clare Elish, Michael Gao, Joseph Futoma, William Ratliff, Marshall Nichols, Armando Bedoya, Suresh Balu, and Cara O'Brien, "'The human body is a black box' supporting clinical decision-making with deep learning," *Proceedings of the 2020 ACM Conference on Fairness, Accountability, and Transparency* (2020): 99-109.

34 ClinicalTrials.gov, "Implementation and Evaluations of Sepsis Watch," identifier: NCT03655626.

Repair in the Wake of Innovation

For decades, the tech industry has loudly celebrated a vision of innovation as “disruptive.” From this perspective, innovations are good when they “disrupt” outdated ways of doing things or thinking about problems. Facebook’s motto of “Move fast and break things,” is just one example of how companies foreground disruption as both a way of organizing work and a slogan for their values. While such disruption can indeed “shake things up” and create new opportunities, disruption can also destabilize existing forms of worker or consumer protection and even due-process.[35] Disruptions in a high-stakes workplace, like a hospital, can lead to confusion, chaos, or even adverse clinical outcomes for patients.[36]

The introduction of Sepsis Watch created both positive and negative disruptions. Sepsis Watch was designed as a way to refocus how and when septic patients were cared for. The system purposely did not follow—it disrupted—an old way of doing things in order to create the conditions for better care. At the same time, Sepsis Watch disrupted existing workflows and social relationships both within and beyond the context of sepsis care. These disruptions created gaps, breakdowns, and miscommunications that needed to be attended to in order for the intervention to work effectively. Those who study the introduction of novel technologies into health care have repeatedly demonstrated that it “takes work to make the network work.”[37] Research on computer-supported cooperative work has demonstrated that such “data work” is critical for aligning the messy, dynamic reality of work practices—in medical contexts

---

35 Danielle Keats Citron and Frank Pasquale, “The scored society: Due process for automated predictions,” *Wash. L. Rev.* 89 (2014): 1; Solon Barocas and Andrew Selbst, “Big data’s disparate impact,” *California Law Review*, 104 (2016): 671; Kate Crawford and Jason Schultz, “Big data and due process: toward a framework to redress predictive privacy harms,” *Boston College Law Review*, 55, 1 (2014): 93–128.

36 Joan S. Ash, Marc Berg, Enrico Coiera, “Some unintended consequences of information technology in health care: the nature of patient care information system-related errors,” *J Am Med Inform Assoc*, 11, 2 (2004):104–112, doi:10.1197/jamia.M1471; Kathleen H. Pine and Melissa Mazmanian, “Institutional logics of the EMR and the problem of ‘perfect’ but inaccurate accounts.” *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing* (2014); 283–294.

37 John Bowers, “The work to make a network work: studying CSCW in action,” *Proceedings of the 1994 ACM conference on Computer supported cooperative work* (1994): 287–298.

and beyond—with the outputs of data-driven technologies like algorithmic models.[38]

Sepsis Watch illustrates how disruption is only one half of the process of innovation. In order for innovation to produce effective change, the work of disruption must be coupled with repair. Focusing on the work of repair prioritizes a set of concerns often overlooked in the context of technical implementation.[39] In turn, accounting for the importance of repair contributes to identifying new forms of economic and social value, and expanding the potential for new technologies to benefit different types of workers more equitably.[40]

Innovations can never be fully realized until they exist in the world, and to exist in the world, they require careful integration into existing contexts. Sociologist Anselm Strauss called this kind of work, "articulation work"[41]—work "that gets things back 'on track' in the face of the unexpected, and modifies action to accommodate unanticipated contingencies."[42] Articulation work can be thought of as a type of repair work, because repair should be understood to include not only the physical repair of broken parts but also the cognitive and social repair of communication, interaction, and even common sense. In this way, repair work is generative of new practices, not merely a way to reconstruct what existed before.

38 Claus Bossen, Kathleen H. Pine, Federico Cabitza, Gunnar Ellingsen, and Enrico Maria Pirae, "Data work in health care: An Introduction," (2019): 465-474. See also: Sarah E. Sachs, "The algorithm at work? Explanation and repair in the enactment of similarity in art data," *Information, Communication & Society*, (2019): 1–17.

39 Steven J. Jackson, "Rethinking repair: breakdown, maintenance and repair in media and technology studies today," *Media meets technology, MIT Press* 68 (2013).

40 Hamid Ekbia and Bonnie Nardi. "Social Inequality and HCI: The View from Political Economy," *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*, ACM (2016), http://doi.acm.org/10.1145/2858036.2858343; Lara Houston, Steven J. Jackson, Daniela K. Rosner, Syed Ishtiaque Ahmed, Meg Young, and Laewoo Kang, "Values in Repair," *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16),* ACM, (2016): 1403–1414, https://doi.org/10.1145/2858036.2858470.

41 Anselm Strauss, Shizuko Fagerhaugh, Barbara Suczek, and Carolyn Wiener, *Social Organization of Medical Work* (Chicago: University of Chicago Press, 1985).

42 Susan Leigh Star and Anselm Strauss, "Layers of silence, arenas of voice: The ecology of visible and invisible work," *Computer supported cooperative work* (CSCW) 8, 1-2 (1999): 9–30.

With this framing, in this section we describe how Sepsis Watch disrupted existing workflows and social relationships in ways that required the attention and labor of repair in order to effectively restore those functional workflows and social relationships, and in effect, a functioning care network. In the first half of this section, we describe these disruptions and in the second half, we describe forms of repair.

Define: repair work

Repair work is a form of labor necessary for sociotechnical innovations to become successful. In the process of integrating new technologies and practices into existing systems, repair work creates new arrangements of technology, people, and practices in order to make the goals of a system possible. In this way, repair is a necessary counterpart to the disruptions produced by innovations. Such disruptions may be productive by creating new pathways to achieve a goal, but only after the power hierarchies and information flows that have also been disrupted have been repaired. As such, repair includes not only the physical repair of broken parts but also the cognitive and social repair of communication, interaction, and even common sense.

The process of repair during innovation is generative because it is not about recovering a status quo, but rather about creating new practices and possibilities. This kind of repair work is necessary, consistently undervalued, and often rendered invisible. Still, it requires creativity, skill, and ingenuity—and should be valued as such. Identifying generative repair work expands our focus from those who initiate or design a project to include those whose work and skill is required to make it function.

Innovation as disruption

Sepsis Watch was designed to supplement, and not replace, the existing diagnostic processes of Emergency Department (ED) physicians. Nonetheless, even as the tool was designed to "stay in the background" in the words of one technologist, the introduction of the tool significantly disrupted the work environment, requiring new workflows and social interactions.

One of the primary ways in which Sepsis Watch created a disruption was by challenging existing institutional power hierarchies. Sepsis Watch became an "occasion for structuring," in the words of organizational sociologist Steven Barley, upsetting an organizational hierarchy and creating the conditions for change.[43] Previously, the hierarchy was clear: doctors diagnose and nurses carry out doctors' orders, a defining aspect of the physician as a high status professional, and a boundary that nurses must continually attend to.[44] With Sepsis Watch, RRT nurses were tasked with conveying the information provided by the deep learning model to the doctors in a way that did not strictly align with this hierarchy. During observation of an RRT shift near the beginning of the Sepsis Watch implementation, several nurses agreed that it was often an uncomfortable interaction. One nurse with over five years ICU experience recounted how when she heard about the workflow, she thought to herself, "Are you kidding me? We're going to call *ED attendings?*" Although no one we interviewed spoke explicitly about the gendered or racialized dimensions of these interactions, both race and gender profoundly shape the histories of the nursing and physician

43 Stephen R. Barley, "Technology as an occasion for structuring: Evidence from observations of CT scanners and the social order of radiology departments," *Administrative science quarterly* (1986): 78–108, doi: 10.2307/2392767.

44 E. C. Apesoa-Varano, "Interprofessional Conflict and Repair: A Study of Boundary Work in the Hospital," *Sociological Perspectives* 56, 3 (2013): 327–349, https://doi.org/10.1525/sop.2013.56.3.327. See also: Andrew Abbott, *The system of professions: An essay on the expert division of labor* (Chicago: University of Chicago Press, 1988); Abram De Swaan, "The reluctant imperialism of the medical profession," *Social science & medicine* 28, 11 (1989): 1165–1170.

professions as well as current power dynamics.[45] The interactions of the Sepsis Watch system challenged explicit hierarchies of professional identities, as well as some of the more implicit and intersectional dimensions of gender, race, and status.[46]

While some RRTs considered it simply a new facet of their job, albeit not a particularly pleasant one, other RRTs felt the violation of traditional hierarchies produced substantial friction. At the beginning, several attendings were reported as being frustrated and harsh. Eric, a young nurse who had been at Duke for two years explained, “I think some of them … there’s a few that are consistently like this [irritated] every time you call. I think they probably just don’t… it’s my assumption, they just don’t like their medical judgment being questioned.” Put bluntly in the words of another nurse, “Initially, I did *not* want to make those phone calls.”

Part of the discomfort or deviation from standard ways of working was that the ED doctors and RRT nurses were in different units on different floors. Not only did they not see each other during Sepsis Watch calls, they also did not have any previous professional interactions. The ED is one of the only units in the hospital where RRTs do not work. Reflecting on the tension near the beginning of the project, Sandra, a nurse who had worked in ICUs for over a decade, said:

> ED physicians … we don’t work with them. We’re not there. We don’t have that relationship with them. They don’t know who we are. They don’t really know what we do. So I think

45 J. R. Elliott and R. A. Smith, “Race, Gender, and Workplace Power,” *American Sociological Review* 69, 3 (2004): 365–386, https://doi.org/10.1177/000312240406900303; Christine L. Williams, “The Glass Escalator: Hidden Advantages for Men in the ‘Female’ Professions,” *Social Problems* 39, 3 (August 1992): 253–267, https://doi.org/10.2307/3096961; M. O. Mosley, “Beginning at the beginning: a history of the professionalization of Black nurses in America, 1908-1951,” *Journal of cultural diversity 2, 4 (1995): 101–9; Keisha Jeffries, “Recognizing history of Black nurses a first step to addressing racism and discrimination in nursing,” The Conversation.com, 2020,* https://theconversation.com/recognizing-history-of-black-nurses-a-first-step-to-addressing-racism-and-discrimination-in-nursing-125538.

46 John F. Dovidio, Kerry Kawakami, and Samuel L. Gaertner, “Implicit and explicit prejudice and interracial interaction,” *Journal of personality and social psychology* 82, 1 (2002): 62; Kimberle Crenshaw. “ Mapping the margins: Intersectionality, identity politics, and violence against women of color,” *Stan. L. Rev.* 43 (1990): 1241.

> for me to be saying … 'I feel like you need to start this patient on antibiotics,' or 'I feel like you need to be giving this patient fluids' or whatever … that wouldn't go down too well. I think if you're working with them, that would be different. If you were like, down, physically down in the ED with them, I think that would be a different case scenario.

Having neither a previous nor current face-to-face relationship with the doctors they were calling was unusual and almost prohibitive to effectively working together.

Other components of the workflow that were disrupted involved rerouting existing flows of information among ED physicians themselves. Every patient in the Duke ED is cared for by a team of clinicians, including resident physicians, attending physicians, nurses, physician assistants, and medical students. The physician who is ultimately responsible for the diagnosis and care of a patient is the attending physician. This is a senior physician who oversees resident physicians, who are less experienced, perhaps only one or two years out of medical school. When a new patient is admitted, a resident will visit and perform an examination, coming up with a diagnosis and course of care. Before proceeding, the resident will talk with the attending, describing the patient and symptoms or other relevant details. The resident explains this information to the attending, who may voice agreement or suggest other options or information to consider. In this way, information is gathered from the patient by the resident and then communicated by the resident to the attending, who either confirms the diagnosis or helps the resident reach an appropriate diagnosis. The resident then communicates this mutually agreed upon information to the patient and in the patient's electronic health record as an official diagnosis and set of orders to be carried out by other clinicians or hospital staff.

Sepsis Watch does not fit neatly into this information cycle. Recall that the RRT nurse communicates the alerts directly to the ED attending. However, in the ED, it is the residents who are more likely to be interacting with patients, and who are the first to propose a diagnosis. The attending is normally the final confirmation of a diagnosis proposed by a resident, but with Sepsis Watch, the resident is passed over and the information is proposed by a nurse to the attending. In practice, this meant that sometimes when an RRT nurse called, an attending had not yet seen the patient or may not yet have had time to become familiar with the patient (because the resident had not yet communicated the information or the attending had not yet done her rounds.)

Moreover, the way that the Sepsis Watch deep learning algorithm generates a risk score for patients is a fundamentally different way of reaching a diagnosis compared to current medical practice.[47] Diagnoses in a teaching hospital like Duke are reached by seeing the patient, drawing on relevant knowledge and experience, and engaging in a diagnostic conversation among colleagues. Sepsis Watch does not involve seeing a patient and was not built to engage in a back and forth diagnostic conversation. Indeed, Sepsis Watch is built around a non-interpretable algorithm, meaning that the tool does not explain *why* a particular risk score was produced, it only displays the score.[48] The score is intended to be one piece of the diagnostic puzzle, and does not direct treatment; the attending physician makes the final diagnosis.

Interestingly, both nurses and doctors alike relied heavily on the language of *seeing* to describe the process of diagnosis and care. When there was a difference between what the deep learning model produced and what the doctor felt to be the diagnosis for the patient, doctors would say things like, “But what are you seeing that I’m not seeing?” RRT nurses also felt limitations to what they could comprehensively know because they were not *seeing* the patients. As one nurse explained:

> I think the difficulty is that when you’re treating patients on the floor, you’re going to see them so you’re actually looking at

47 Rob Kitchin, "Big Data, new epistemologies and paradigm shifts," *Big data & society* 1, 1 (2014): 2053951714528481; Sabina Leonelli, "What difference does quantity make? On the epistemology of Big Data in biology," *Big data & society* 1, 1 (2014): 2053951714534395; Brent Daniel Mittelstadt and Luciano Floridi. "The ethics of big data: current and foreseeable issues in biomedical contexts," *Science and engineering ethics* 22, 2 (2016): 303–341.

48 The first author and the DIHI team described the processes de-emphasizing explainability in favor of other mechanisms of accountability in a previous article: Sendak et al., "’The human body is a black box.’”

> them and you're looking at the big picture. I think the problem is, we're just calling down. We don't see the patient down there, so it's kind of that disconnect.

Both RRT nurses and ED physicians often found the exchange of information challenging. A typical story about a phone call was recounted to us by Ashley, a young nurse with two years of experience in ICUs:

> I'll say [the patient] is popping up as high-risk of sepsis. And [the doctor] will be like, 'Well why, why does it say they're high-risk because they don't look septic here.' You know, obviously, I don't know exactly why the app is populating them that way so I think if they understood that we don't have all the bits of information that are making [the patient] a red card or a black card or yellow or orange … I just have how the computer model populates them into which color and I'm kind of going from there.

When the overall workflow was being designed by the DIHI team and project clinicians, it was assumed that communication from the RRT nurse about the patient to the ED physician would be a relatively straightforward transfer of information. In practice, and in order for the information to be meaningfully incorporated into care practices, who was communicating with whom and how was no simple matter. The new kinds of communication set in motion by Sepsis Watch often presumed relationships that did not exist—and yet that were required for Sepsis Watch to work as intended.

Additionally, the introduction of and response to Sepsis Watch brought to the surface the distinct perspectives and priorities of different teams. Because Sepsis Watch required parts of the organization to coordinate and cooperate in unprecedented ways, the fact that different teams had different "definitions of the situation" became clear, underscoring the importance of accounting for the different standpoints from which actors in a social situation make sense of what they do and why they do it.[49] In this case, these

49 Sandra Harding, ed.,*The Feminist Standpoint Theory Reader: Intellectual and Political Controversies* (New York: Routledge, 2004).

differences existed well before the introduction of Sepsis Watch, but became newly consequential when different teams needed to work together. The differences help explain why the attitudes and behaviors of each group involved with the system varied widely.

For instance, sepsis was of the utmost importance to clinical leadership. This key group of stakeholders includes high status physicians and administrators who were involved in hospital-wide management decisions. It is this group of individuals who most likely would be responsible for ensuring that patient care, in the aggregate, improved and could be demonstrated through existing metrics of care quality like sepsis bundle compliance.

In contrast, sepsis competed with more visible priorities for the average ED physician. In response to questions about how much sepsis comes up in the Emergency Department, one ED nurse who had been working at the hospital for two years shrugged her shoulders, and confided, “Down here [in the ED], we’re dealing with, like, emergencies—bones and psych patients ... We’re just trying to get them stabilized as quickly as possible and move them to another unit.”

Moreover, the majority of doctors we interacted with during observations felt like Sepsis Watch was not really necessary, because they did not feel diagnosing and treating sepsis was a problem in the department. This widespread *perception* stands in contrast to the hospital’s internal data, which showed a need to improve the diagnosis and management of sepsis in the ED.

The contrast between individual physicians’ perceptions of how much of a problem sepsis was compared to the hospital’s aggregated data illustrates a complex tension: Are analytics a measure of actual care or of performative compliance? In several interviews with physicians, they expressed a general mistrust of bureaucratized protocols when applied to their own individual clinical practice.[50] Many, though not all, ED physicians felt not only that diagnosing and treating sepsis was not a problem in the ED, but also that parts of the Centers for Medicare and Medicaid Services (CMS) sepsis guidelines were potentially misguided. In the words of Raj, a new attending:

> The [bureaucratically required task] that really, that really gets in my way is the fluid recommendations, because to me an attending ER physician is better at assessing how much fluids the patient needs than a set number. … That's the reason why you have a human provider and not a computer provider. We're the ones that are to be making that decision and not CMS recommendations.

For this physician, and many others we interviewed, their definition of the situation prioritized "physician autonomy" not only as a professional value but also a prerequisite for appropriate care and even a hallmark of operating effectively as a physician. For them, structures of compliance limited their ability to do their job well, and Sepsis Watch represented a way in which their professional discretion was being limited and their ability to care for patients was being undermined. Moreover, not only was Sepsis Watch an imposition of centralized standards, there was also an implication that doctors' existing practices needed to be fixed by remotely located nurses.

That different actors and teams inhabit different standpoints and have different definitions of the situation is not necessarily problematic. What is salient here is that Sepsis Watch not only forced a reckoning of these different perspectives, but also attempted to *impose* a set of priorities (those of senior hospital leadership as mediated by the Sepsis

50 Such dynamics are common and are an important area of study at the intersection of technology, health care, and organizations. For example, see: Stefan Timmermans, Marc Berg, *The gold standard: the challenge of evidence-based medicine and standardization in health care* (Philadelphia, PA: Temple University Press, 2003); Trisha Greenhalgh, Henry WW Potts, Geoff Wong, Pippa Bark, and Deborah Swinglehurst. "Tensions and paradoxes in electronic patient record research: A systematic literature review using the meta-narrative method," *The Milbank Quarterly* 87, 4 (2009): 729–788.

Watch team, who in turn had their own definition of the situation) that were only variously aligned with the priorities of different parts of the organization. In this imposition we can locate disruptive and destabilizing dynamics that require repair.

Repair as innovation

Everyone involved with developing or integrating Sepsis Watch into effective clinical care carried out essential repair work in the wake of the disruptions and destabilizations created by the system's introduction. But more than anyone else, the RRT nurses who monitored the Sepsis Watch app developed key forms of repair work that allowed the system to succeed. This work often involved drawing on the nurses' existing knowledge of the hospital and trying to produce *ad hoc* solutions. "Workarounds" following implementation of new processes or technologies are a common and widely studied phenomenon in the health care domain.[51] However, as scholars Kathleen Pine and Melissa Mazmanian argue, it is important to understand such practices not merely as temporary or casual forms of work but instead as skilled and essential forms of coordination.[52] Throughout the six-month pilot, RRT nurses carried out various forms of repair work, integrating Sepsis Watch into organizational hierarchies, norms, and workflows in ways that were both unanticipated and essential.

One form of repair work was mediating the professional hierarchies and traditional workflows that had been disrupted. For instance, the RRTs developed techniques to time their calls appropriately for the "rhythmscape"[53] of the hospital, accounting for the importance and experiences of time in how organizations function effectively,

51 Rob Procter, Joe Wherton, Trish Greenhalgh, Paul Sugarhood, Mark Rouncefield, and Sue Hinder, "Telecare call centre work and ageing in place," *Computer Supported Cooperative Work (CSCW)* 25, 1 (2016): 79–105.

52 Kathleen H. Pine and Melissa Mazmanian, "Artful and contorted coordinating: The ramifications of imposing formal logics of task jurisdiction on situated practice," *Academy of Management Journal* 60, 2 (2017): 720–742.

53 Melissa Cefkin, "Numbers may speak louder than words, but is anyone listening? The rhythmscape and sales pipeline management," *Ethnographic Praxis in Industry Conference Proceedings*, 2007, 1 (Oxford, UK: Blackwell Publishing Ltd, 2007): 187–199.

an important theme for organizational scholars.[54] For instance, Eric explained that one thing that has "a huge effect" on how responsive doctors will be to the calls "is shift change. So I know what time they change shifts. I'm not gonna call 45 minutes before ... it's like they've mentally checked out. I've never had anybody willing to [engage]; they don't want to talk." RRTs also developed a practice of grouping calls together by pods—the term used to describe the subdivisions of the ED that are managed by one care team. Before calling about a high-risk patient, they would conduct a triage review of all the existing patients in the app to see where all the patients were located. This way, rather than calling about one patient, and then calling back 10 minutes later about another, they could bundle the patients into one conversation so that the doctors were not overloaded—or annoyed—by constant calls.

RRTs managed time not only as a strategy of efficiency but also as a form of respecting professional autonomy. For instance, they monitored what was happening with a particular patient and what the clinicians were doing before calling down to remind them about required protocol steps. "I'll give [the ED nurse] a little bit of time like, you know, if [the doctor] really just prescribed the antibiotics and it's still within the timeframe, I'll give them some time 'cause, again, I know they're busy and they've got other things to do." Another RRT nurse, Tracy, explained,

> Most [care providers] are also very kind and they're happy to hear from us. Sometimes they're busy. I notice it's nice and they appreciate it when I start the conversation off with hey, you know, I'm [person's name], I'm RRT nurse working the sepsis watch tonight, I want to talk with you about a patient or two patients or whatever it is. Is this a good time to talk? … I notice that's been helpful. I think they're more receptive to me if I at least offer, is this is a good time to talk? Most of the time they say yes, sometimes they say no and then I'll say, can I call back in 15 minutes?

54 Wanda J. Orlikowski and JoAnne Yates, "It's about time: Temporal structuring in organizations," *Organization science* 13, 6 (2002): 684–700; Melissa Mazmanian, Ingrid Erickson, and Ellie Harmon, "Circumscribed time and porous time: Logics as a way of studying temporality," *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing* (2015): 1453–1464.

These kinds of strategies were not in the original workflow designs, but were key to effectively asking for doctors' time and attention. When the DIHI team was originally planning to support the new workflow, they prepared scripts that the RRTs were encouraged to use when making phone calls. They weren't required; they were suggested to facilitate the conversation. The scripts were straightforward, representing what the DIHI team, including the clinician leads and ED representatives, thought would be needed. In fact, they had been created as a means to reduce the amount of work RRTs would need to do in order to make the phone call. However, the knowledge and expertise of the RRTs was irreplaceable. None of these scripts included the strategies that the RRT nurses would ultimately use to effectively communicate with the ED physicians.

In addition to managing call timing, RRTs developed additional techniques to mitigate the annoyance that many doctors felt. One nurse explained how she had developed a way to effectively probe what she might need to do in the conversation:

> In a typical interaction I always start the same way. 'Hi, this is [person's name]. I'm the RRT nurse from Sepsis Watch. How are you?' I ask how are you so that I can immediately get a feel of whether or not they're busy and want to talk. ... And even though I know they don't want to waste time with 'how are you,' it gives me an indication of how this call's gonna go.

This example was one of many where RRT nurses developed techniques involving a great deal of what Arlie Hochschild called "emotional labor," constantly negotiating their tone and approach based on the affective reactions of the doctors they called.[55] "Emotional labor" refers to the planning, management, and display of feelings and emotional expressions at work to facilitate organizational goals and norms, often supplementing other forms of physical and cognitive labor. While emotional labor is a critical component of many jobs, it is stereotypically gendered as female and lower-status work, and is associated with lower wages.[56]

55 Arlie Russell Hochschild, *The managed heart: Commercialization of human feeling*, (University of California Press, 2012).

56 Theresa M. Glomb, John D. Kammeyer-Mueller, and Maria Rotundo, "Emotional labor demands and compensating wage differentials," *Journal of applied psychology* 89, 4 (2004): 700, doi:10.1037/0021-9010.89.4.700. PMID 15327355.

In order to integrate Sepsis Watch into the clinical workflow of ED clinicians, RRT nurses not only managed their own displays of emotion, but also found ways to inspire feelings in others. This emotional labor became a form of repair work, in which their affective management of the situation enabled an effective exchange of information. Another nurse, Kim, explained:

> When I usually call, I introduce myself and say I'm with Sepsis Watch and then mention that there's a patient that, per Sepsis Watch, is meeting or at high-risk for sepsis. And I just kind of ask their opinion, "Is that something that's … on the differential or you're looking into?" … I think initially some of the wording [from the original workflow sheet] could seem a little accusatory to them, and be like "This patient is probably septic. Have you done anything yet?" or things like that. I kind of learned to just be more open-ended with the conversation… to say "Hey, this patient on our end is populating as they could be septic. Is that something you're thinking as well, or not?"

Here, the RRT nurse is careful to say what she is seeing on "our end," meaning from the perspective of Sepsis Watch. This kind of careful delineation of work boundaries was another form of repair work that RRTs undertook. To bridge the "disconnect" between the ED and Sepsis Watch, both interpersonally and diagnostically, RRT nurses created and maintained the boundaries of their "professional scope of practice." RRT nurse Tracy emphasized, "It's not in our scope of practice to make recommendations. I'm not a doctor, that's not within my jurisdiction to tell you what to do." RRT nurses described the motivation to do this boundary-work variously as "not trying to overstep," and "to staying in my lane."

Reflecting on the positive change in the typical Sepsis Watch call over the previous months, RRT nurse Ashley said, "I think [ED physicians are] now realizing that it's just a tool to make sure that if we are gonna treat for sepsis that the tasks are being completed within the timeframe that we need them to be as opposed to us making sure that they are treating sepsis correctly. I think they're realizing we're not here to contraindicate your diagnosis. We're just here to manage the time." The calls were more effective in part because the repair work of the RRTs had created a new way to bound their work—doctors were in charge of judgment and nurses were there to track the logistics of timing and execution.

At the same time, another form of repair work performed by the RRTs involved stitching together justifications for the risk score so that it could be integrated into the diagnostic communication flow, something not clearly within their scope of practice. In order for Sepsis Watch to be effective, the tool's outputs and the diagnostic practices of the ED had to be woven together, and this work of stitching together fell on the RRTs. This became most clear in the ways in which the RRTs researched and prepared for their conversations with the ED physicians.

Every RRT started to do a "chart review" on patients before calling down to the Emergency Department. Sitting at their computer workstation, an RRT would pull up the electronic health record of patients and review their histories and current conditions, something that the ED clinicians downstairs in the ED would also be doing as part of their care. In this way, the RRTs contextualized the risk score, both for their own understanding as well as to more effectively communicate with the treating physicians. That RRT nurses began doing this was a surprise to the DIHI development team, because this had never been articulated as part of the workflow or planned in the design. However, contextualizing the risk score facilitated more nuanced conversations with physicians. As one nurse explained, he found it important to make clear that he's knowledgeable about the patient.

Some RRTs performed even more due diligence before calling, reviewing and tracking the charts of medium-risk patients, or anticipating potential pushback from physicians. As one nurse explained, "As I start to do a chart review, I look at it in the sense of proving to me it's not [going to be sepsis]." Those RRTs who felt the responsibility to most effectively communicate described gathering evidence from the chart to support the risk score generated by the Sepsis Watch model. With this information, the RRT could engage in a diagnostic conversation more akin to a traditional clinical exchange. These RRTs found that many doctors would want to know why the score was coming up as it was if they weren't "seeing it" in the patient. Armed with contextualized details about the patient and potential hypothesis, the RRTs and doctors could more effectively engage each other.

However, in the particular case of justifying the risk score, the repair work created a new kind disconnect. On one hand, the repair work, necessary in the wake of disruption, ultimately made the implementation of Sepsis Watch successful and allowed more high-risk patients to be treated. On the other hand, the rationales and explanations that RRT nurses were developing were not always accurate. While every RRT nurse we spoke with understood that Sepsis Watch *predicted the risk* that someone would develop sepsis (as opposed to actually *diagnose* sepsis), many RRTs misunderstood how the model arrived at the risk score.

One nurse explained during an observation that he thinks "it is looking for keywords" in the medical record, which is not the case. Others pointed to specific lab tests as being criteria for Sepsis Watch to generate a high risk score. While lab tests are variables taken into account by the model, citing a lab test as causing the risk score is an inaccurate description of how the model works. In this case, this inaccuracy didn't negatively impact the tool's use. Exploring the implications of this dynamic with regard to debates around explainability and AI are important, but beyond the scope of this report.[57] Salient for our discussion here is that such repair work was necessary and occurred, but the ways in which it occurred may have had unintended consequences.

The repair work of the RRTs reveals implicit and explicit forms of expertise. The RRT nurses exercised their varied forms of expertise in order to effectively integrate Sepsis Watch as they applied their knowledge of organizational rhythms, performed

57 When our research began to bring these practices to light, the DIHI team made changes to the interface and to the educational materials around Sepsis Watch in order to correct these misattributions of cause. Over the course of Sepsis Watch's development, the need to justify, explain, and trust a "black box" deep learning system was a constant focus as a design and responsible innovation challenge. The first author and the DIHI team explored these issues in a previous article: Sendak, et al., "'The human body is a black box.'"

emotional labor in order to facilitate interactions with harried and skeptical doctors, and leveraged their clinical expertise by engaging in diagnostic conversations. The RRTs also became experts in the care of sepsis, itself. As Jennifer, a nurse who had worked at Duke for only a year but had worked in other ICUs for over 15 years, explained:

> It's really, it's been enlightening and I think … the RRT role doesn't just feel like you're a rapid response nurse, right? Like, you are a sepsis watch nurse. Like you are watching sepsis ... in the ED. And it's cool, you know, it's a totally new job title under the RRT role. And a new responsibility—one I welcome. I think it's really good. And I think having a nurse with good clinical judgment, hopefully, as being that second check [is important], right?

To be sure, not every RRT nurse found the new role and responsibilities enjoyable or satisfying. Some we spoke with felt that it took away from their primary duties of bedside care, echoing a common concern among nurses as ever more sophisticated technologies enter the hospital and demand their attention.[58] In fact, all the nurses we spoke with were very careful to differentiate what they were doing with Sepsis Watch as being distinct from providing clinical care, which they understood to necessarily involve physically seeing patients.[59] Nonetheless, many embraced the new work, finding an interesting challenge.

It's important to note that much of the repair work we describe was possible because the autonomy of the RRT nurses was respected. As trained intensive care nurses, they were clinicians with clinicial decision-making experience and expertise. The RRTs had been allowed professional discretion—to make decisions about how to carry out their responsibilities—and in

58 For a study of the long and inextricable history of nurses and medical technologies, see: M. Sandelowski, *Devices and Desires: Gender, Technology, and American Nursing* (Chapel Hill, NC: University of North Carolina Press,2000).

59 The ways in which nurses conceptualize and practice care is an important area of study, and beyond the scope of this report. For a fascinating ethnography of nurses and tensions around care see: Daniel F. Chambliss, *Beyond caring: Hospitals, nurses, and the social organization of ethics* (University of Chicago Press, 1996).

turn, the flexibility to improvise and create the conditions and tactics of effectively communicating the risk scores produced by Sepsis Watch. The repair work performed by the RRTs could be effective and for many, empowering, because their professional discretion and expertise was supported, not undermined, by the team developing Sepsis Watch.

Evidence-based Interventions: **a Double-edged Sword**

The stakeholders directly implicated in Sepsis Watch varied in the degree to which they embraced Sepsis Watch as an effective intervention. In this report, we've mainly focused on one set of stakeholders, RRTs, but in this section we expand our perspective in order to examine some of the limitations and additional resistance facing the technology's implementation.

Some physicians called into question whether compliance analytics (i.e., tracking whether sepsis CMS bundles were completed in the correct amount of time) could or should be used as a proxy for patient care. For instance, one physician, Arthur, pointed out that an improved compliance with sepsis care protocols might not necessarily mean improved patient outcomes. Before really trusting the value of the system, he wanted a clear connection to data tracking patient mortality rates. From the perspective of the developers, patient mortality was not a metric they were using to assess the success of Sepsis Watch. Prior to implementation, the team had prioritized picking a metric that accurately reflected the specific intervention that Sepsis Watch had been designed to address: improving sepsis protocol compliance within the CMS mandated timeframe. In this way, the team's goal could be as discrete and defined as possible and enable more accurate evaluation.

The goal of improved compliance was chosen because improving compliance is demonstrated to lead to better patient outcomes. However, improved compliance is not necessarily the same thing as improved patient outcomes. Several doctors pointed out that for some patients who were already overloaded on fluids, they didn't feel comfortable pushing the extra fluids required to formally complete the protocol. They might do every other step of the protocol, except push more fluids, because in their judgment, that was the best care for the patient. In this hypothetical scenario, the patient's health might improve, but the doctor's care would have failed to comply with the standard protocol. To complicate the matter, protocol compliance is not simply a matter of individual patient health. Rates of protocol compliance, for sepsis as well as many other diseases, impact the rates of reimbursement hospitals receive from Medicare as well as the relative rankings of quality of care at different institutions. The needs and motivations for standardized care are complex, to say the least.

The concern from these doctors was that if compliance with a standard is the only thing being measured, there is the possibility of missing the goal that the compliance was originally aiming to meet. By analogy, was this tool improving education or simply teaching to the test?

The clinical leads on the project and clinicians who supported this intervention emphasized that the health-care community operates on the general consensus that evidence-based guidelines improve patient care. Standards are not perfect, but they are the best way forward. That a tool like Sepsis Watch aims to increase compliance with evidence-based guidelines should generally be considered a net positive.

Nonetheless, the concerns of these doctors point toward a set of ongoing tensions implicated in integrating AI systems into health care: On a primary level, measuring what an intervention does and does not do must be tightly coupled to what the model and the data represent. This tension also underscores the importance of specifying and measuring the right goal at the beginning of the project. Additionally, the tension between analytics as a measure of *compliance* versus a measure of *care* points toward the need to fully account for how new technologies may ossify existing guidelines or rules in unexpected ways, even though such guidelines may be misguided or may not be appropriate for every patient.[60] The risk is that new forms of automation risk over-writing the local ways in which workers exercise flexibility and professional discretion.[61] In the case of Sepsis Watch, decisions about patient care were left to the discretion of the attending physician, and we saw how the Sepsis Watch system design also created space for nurses to exercise discretion. However, future technologies will not necessarily respect clinician autonomy.

60 Timmermans and Berg. *The gold standard*; Trisha Greenhalgh, Jeremy Howick, and Neal Maskrey, "Evidence based medicine: a movement in crisis?" *The BMJ* 348 (2014); Robert Aronowitz, *Risky medicine: our quest to cure fear and uncertainty* (Chicago: University of Chicago Press, 2015).

61 Katherine C. Kellogg, Melissa A. Valentine, and Angèle Christin, “Algorithms at Work: The New Contested Terrain of Control,” *Academy of Management Annals 14, 1 (2020).*

Finally, while many stakeholders understood this as a technology-enabled solution, others wondered if it was simply a success based on resource allocation. Were patients receiving better care because of the predictive capacity of the model, or because a nurse was calling a physician, essentially reminding them to think about and quickly treat sepsis? Given the existing reality that high-tech and data-driven interventions attract attention and resources, it is likely that without Sepsis Watch, the resources to pay and support the RRT nurses' time might not have been allocated. The needs of the Sepsis Watch project justified the reallocation of resources in ways that might not have been possible otherwise. Reflecting on this dynamic, one nurse commented, "It's like if you nag your husband to take out the trash. And he says, 'I was already going to take out the trash!' And the fact is, maybe he was. Maybe he wasn't. But at the end of the day, the trash got taken out."

Looking to the Future of AI in Routine Clinical Care

Technologies hold great promise to address some of the world's most pressing problems, but without careful integration into our existing social worlds, they risk failure at best and harmful consequences at worst.[62] In health care, AI-driven interventions have the potential to enhance people's lives—but they will not do so automatically or uniformly. Along every step of development, from problem formulation to dataset selection to validation and implementation, there are consequential choices that shape how and how well a technology will work. There is a growing field of research examining the challenges and best practices facing AI development. However, there remains relatively little focus on the challenges and opportunities facing AI *implementation* and what is required to responsibly take an innovation from the lab or boardroom out into the world.

This report has examined the implementation of Sepsis Watch into the Duke Emergency Department as a way to examine some of the challenges and opportunities that arose when an AI-driven intervention was actually used in a clinical context. By framing Sepsis Watch as a complex sociotechnical system, not just a machine learning model, this report brings into focus the critical role of human labor and organizational context in developing an effective clinical intervention. Our research demonstrates that it is more than the model and data that make an intervention work; an intervention becomes effective through complex sets of people, practices, technologies, and infrastructures. Taking a sociotechnical view reveals that the social dimensions of an intervention are fundamental to how these systems actually work and how they can fully address the problems they've been designed to solve.

62 Kashmir Hill, "Wrongfully Accused by an Algorithm," *The New York Times, June 24, 2020,* https://www.nytimes.com/2020/06/24/technology/facial-recognition-arrest.html; Joy Buolamwini and Timnit Gebru, "Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification," *Proceedings of Machine Learning Research 81 (2018): 1–15; Virginia Eubanks, Automating inequality: How high-tech tools profile, police, and punish the poor (New York: St. Martin's Press, 2018);* Julia Angwin, Jeff Larson, Surya Mattu, and Lauren Kirchner, "Machine bias: There's software used across the country to predict future criminals. And it's biased against blacks," ProPublica, 23 (2016). Frank Pasquale, *The black box society: The secret algorithms that control money and information* (Cambridge, MA: Harvard University Press, 2015).

Moreover, in this report, focusing on these social dimensions of the system revealed an underappreciated aspect of innovation: When innovations disrupt, there must also be repair to realize effective functioning in the world. Repair does not re-establish a status quo, but rather creates a new set of practices that brings into being the full extent of possibilities imagined for a technology.

Prioritizing the work of repair, in this case carried out by the RRT nurses, shifts our focus from those who initiate a project to those whose work and skill is required to make it function. Valuing the work of repair and the individuals who perform it expands traditional conceptions of where innovation occurs and what it looks like, drawing attention to new kinds of necessary expertise. In this expanded conception, it is not only the work of computer scientists and engineers, kinds of elite work typically gendered male and predominantly white, that can be seen as key to innovation. Rather, it is the skills and expertise of frontline workers, in this case nurses, who repair what has been disrupted and enable the system to work effectively in the world. The value of this work must be recognized and supported in every AI-driven intervention.

In many ways, Sepsis Watch was a successful sociotechnical implementation of AI into health care. But we also need to keep in mind the limitations and open questions raised by this intervention. To explore a problem sociotechnically also means to be aware of the ongoing social dimensions of the system and even the problem itself.

One important set of questions and potential limitations involves the use of electronic health data and the potential to introduce or re-entrench racial disparities in health care. Electronic health records are the data foundation upon which Sepsis Watch, and many other AI and data-driven interventions, are built. However, uncritical use of electronic health records data will entrench and perpetuate existing health inequities.[63] In the United States, the COVID-19 pandemic has laid bare the profound disparities in health and health care facing Black, Hispanic, and Indigenous communities.[64] AI and data-driven interventions must acknowledge these disparities and actively mitigate them. What this acknowledgement, mitigation, and intervention looks like in practice is a crucial area to develop and study.

Another set of research questions revolves around the medium- to long-term effects of implementing AI systems for clinician expertise, and how this might change professional practice and medical education. The research presented in this report took place at the early phases of introducing a new technology. Even over the months during which we conducted interviews, attitudes and work practices shifted. Early studies of the use of robotics in surgery demonstrate significant changes in the ways in which surgeons learn and practice their skills.[65] In the case of systems that combine clinical expertise and machine learning prediction, like Sepsis Watch, there is the potential to introduce over-reliance on the AI technology or even deskilling.[66] The feedback loops, both expected and unexpected, between human expertise and machine prediction need to be closely examined and refined.

63 Ziad Obermeyer, Brian Powers, Christine Vogeli, and Sendhil Mullainathan, "Dissecting racial bias in an algorithm used to manage the health of populations," *Science* 366, 6464 (2019): 447–453; Milena A. Gianfrancesco, Suzanne Tamang, Jinoos Yazdany, and Gabriela Schmajuk, "Potential biases in machine learning algorithms using electronic health record data," *JAMA internal medicine* 178, 11 (2018): 1544–1547; Kun-Hsing Yu and Isaac S. Kohane, "Framing the challenges of artificial intelligence in medicine," *BMJ quality & safety* 28, 3 (2019): 238–241; Merlin Chowkwanyun and Adolph L. Reed Jr., "Racial health disparities and Covid-19—caution and context," *New England Journal of Medicine* (2020); Zinzi D. Bailey, Nancy Krieger, Madina Agénor, Jasmine Graves, Natalia Linos, and Mary T. Bassett, "Structural racism and health inequities in the USA: evidence and interventions," *The Lancet* 389, 10077 (2017): 1453-1463; Kadija Ferryman and Mikaela Pitcan, *Fairness in Precision Medicine*. (New York: Data & Society Research Institute, 2018).

64 Chowkwanyun and Reed, "Racial health disparities and Covid-19; Clyde W. Yancy, "COVID-19 and African Americans," *Jama* (2020).

65 Matthew Beane, "Shadow Learning: Building Robotic Surgical Skill When Approved Means Fail," *Administrative Science Quarterly* 64, 1 (2019): 87–123, https://doi.org/10.1177/0001839217751692.

66 Federico Cabitza, Raffaele Rasoini, and Gian Franco Gensini, "Unintended consequences of machine learning in medicine," *Jama* 318, 6 (2017): 517–518, doi:10.1001/jama.2017.7797.

Moreover, the dynamics of disruption and repair and the work of building trust in the context of remote care will be increasingly relevant as health care shifts in response to COVID-19. For instance, how will more remote tele-health conversations and consultations shift the work of care? What kinds of repair work will clinicians need to perform to effectively care for patients? How can design and implementation processes best support this repair work, and how can new projects enact principles of design justice?[67]

With this report and its focus on the repair work that is required in the wake of disruptive innovation, we hope to have demonstrated that these questions and the many others facing the future of AI in health care must be understood as more than questions of models or datasets. Examinations of interventions in situ, in their cultural and institutional context, are essential in order to understand the full range of consequences and implications.

67 Sasha Costanza-Chock, *Design justice: Community-led practices to build the worlds we need (Cambridge, MA: MIT Press, 2020).*

APPENDIX: METHODS

The research described in this report, from research design to final analysis and writing, was conducted over the course of two-and-a-half-years years, from the winter of 2017 to the summer of 2020. The project began when the primary researcher, Madeleine Clare Elish, was introduced to the project lead at DIHI, Mark Sendak, through a mutual acquaintance. Over the spring and summer of 2017, a research collaboration between Data & Society and DIHI was agreed upon to investigate the socio-cultural dimensions of implementing Sepsis Watch.

The motivating research question was focused on how professional roles change or are reconfigured through the introduction of a computational "intelligent" agent in a health-care setting. To address this question, the primary researcher conducted research and field visits with the support of independent philanthropic grants to Data & Society. There was no financial arrangement between Data & Society and DIHI. Before any human subjects research began, an Institutional Review Board protocol was developed and approved by the Duke University Health System Institutional Review Board (Pro00093721 DUHS).

Research at DIHI and Duke Hospital was carried out by the primary researcher and an undergraduate researcher, Sahil Sandu, and included on-site semi-structured interviews as well observations of clinical practice and hospital administrative meetings. In total, 37 semi-structured interviews were conducted: 7 technologists, 17 physicians, and 13 nurses. The primary researcher also observed 29 hours of clinical practice: 13 hours shadowing RRTs, and 16 hours shadowing clinicians in the ED. Race and demographic data was not collected in order to protect the anonymity of research participants.

Data analysis and coding were conducted by the primary researcher and a graduate research assistant, Elizabeth Anne Watkins. Both researchers separately read through the interview transcriptions and field notes, using guidelines drawn from grounded theory analysis.[68] Together, they discussed emergent themes and related literature from the fields of organizational sociology, science and technology studies, technology adoption in health care, and feminist epistemology. These discussions elucidated shared observations on reconfigurations to professional roles and organizational routines, and in particular the emergence of novel kinds of labor. As findings began to coalesce, researchers also concurrently consulted with relevant literature in an iterative, back-and-forth process. From these discussions, researchers then chose a set of thematic patterns, at which point they revisited previously analyzed data to further strengthen their analysis with additional empirical insights.

At the conclusion of field research and an initial period of analysis, early findings were presented to DIHI and to clinicians involved in the project, with their feedback further shaping the analysis. Over the course of developing the report, the research was also presented at 4S and the AI100 workshop on "Prediction in Practice" at Cornell Tech, and workshopped with the Data & Society Raw Materials Seminar and the Algorithmic Fairness & Opacity Group at University of California, Berkeley.

68 Matthew B. Miles and A. Michael Huberman, *Qualitative data analysis: An expanded sourcebook* (SAGE Publications, 1994); A. Strauss, and J. Corbin, "Grounded theory methodology," *Handbook of qualitative research* 17, 1 (1994): 273–285.

ACKNOWLEDGEMENTS

This research was conducted with support from Luminate, the Ethics and Governance of AI Fund, and the John D. and Catherine T. MacArthur Foundation. The project would not have been possible without the team at the Duke Institute for Health Innovation, and we cannot thank enough Mark Sendak, Will Ratliff, Suresh Balu, Cara O'Brien, and Armando Bedoya, as well as Dina Sarro and Liz Alderton. Special thanks to Sahil Sandu for the spectacular research and interviews that contributed to this report. We also would like to thank all the people who supported and helped us during fieldwork at Duke Health including Jason Theiling, Corey Miller, Dustin Tart, Kelly Kester, Holly Glover, Liset Dennis, Joe Futoma, and all the clinicians we shadowed in the ED and on 7700. We are grateful to Katie Pine, Angèle Cristin, Steven Jackson, Sareeta Amrute, danah boyd, and Janet Haven for their insightful comments on previous drafts.

We would also like to thank the interview participants who shared their time and experiences with us, and we would like to extend our gratitude to the patients who allowed us to shadow the clinicians caring for them and be present during vulnerable times in their lives.

Last but certainly not least, we thank Patrick Davison for being the brilliant shepherd of this project and for being a partner in thought and writing, as well as Yichi Liu, Natalie Kerby, Sam Hinds, Chris Redwood, and the staff members at Data & Society whose work and expertise make this report possible.

REFERENCES

Abbott, Andrew. *The system of professions: An essay on the expert division of labor*. Chicago: University of Chicago Press, 1988.

Angus, Derek C., Christopher W. Seymour, Craig M. Coopersmith, Clifford Deutschman, Michael Klompas, Mitchell M. Levy, Greg S. Martin, Tiffany M. Osborn, Chanu Rhee, and R. Scott Watson. "A framework for the development and interpretation of different sepsis definitions and clinical criteria." *Critical care medicine* 44, no. 3 (2016): e113

Anteby, Michel, and Curtis K. Chan. "A self-fulfilling cycle of coercive surveillance: Workers' invisibility practices and managerial justification." *Organization Science* 29, no. 2 (2018): 247-263

Aronowitz, Robert. *Risky medicine: our quest to cure fear and uncertainty.* University of Chicago Press, 2015.

Ash, Joan S. Marc Berg, Enrico Coiera. Some unintended consequences of information technology in health care: the nature of patient care information system-related errors. *J Am Med Inform Assoc.* 2004;11(2):104-112. doi:10.1197/jamia.M1471

Bailey, Zinzi D., Nancy Krieger, Madina Agénor, Jasmine Graves, Natalia Linos, and Mary T. Bassett. "Structural racism and health inequities in the USA: evidence and interventions." *The Lancet* 389, no. 10077 (2017): 1453-1463.

Barley, Stephen R. "Technology as an occasion for structuring: Evidence from observations of CT scanners and the social order of radiology departments." *Administrative science quarterly* (1986): 78-108. doi: 10.2307/2392767

Beane, Matthew. "Shadow learning: Building robotic surgical skill when approved means fail." *Administrative Science Quarterly* 64, no. 1 (2019): 87-123.

Bedoya, Armando D., Meredith E. Clement, Matthew Phelan, Rebecca C. Steorts, Cara O'Brien, and Benjamin A. Goldstein. "Minimal impact of implemented early warning score and best practice alert for patient deterioration." C*ritical care medicin*e 47, no. 1 (2019): 49.

Bossen, Claus, Kathleen H. Pine, Federico Cabitza, Gunnar Ellingsen, and Enrico Maria Piras. "Data work in health care: An Introduction." Health Informatics Journal 25: 3 (2019): 465-474. doi.org/10.1177/1460458219864730. PMID: 31405353

Bowers, John. "The work to make a network work: studying CSCW in action." *In Proceedings of the 1994 ACM conference on Computer supported cooperative work*, pp. 287-298. 1994.

Bowker, Geoffrey C. and Susan Leigh Star. *Sorting things out: Classification and its consequences*. Cambridge: MIT Press, 2000.

Cabitza, Federico, Raffaele Rasoini, and Gian Franco Gensini. "Unintended consequences of machine learning in medicine." *Jama* 318, no. 6 (2017): 517-518. doi:10.1001/jama.2017.7797

Cefkin, Melissa. "Numbers may speak louder than words, but is anyone listening? The rhythmscape and sales pipeline management." In *Ethnographic Praxis in Industry Conference Proceedings*, vol. 2007, no. 1, pp. 187-199. Oxford, UK: Blackwell Publishing Ltd, 2007.

Chowkwanyun, Merlin, and Adolph L. Reed Jr. "Racial health disparities and Covid-19—caution and context." *New England Journal of Medicine* (2020).

Citron, Danielle Keats, and Frank Pasquale. "The scored society: Due process for automated predictions." *Wash. L. Rev*. 89 (2014): 1.

Cohen, Jonathan, Jean-Louis Vincent, Neill KJ Adhikari, Flavia R. Machado, Derek C. Angus, Thierry Calandra, Katia Jaton et al. "Sepsis: a roadmap for future research." *The Lancet infectious diseases* 15, no. 5 (2015): 581-614. Doi:10.1016/S1473-3099(15)70112-X

De Swaan, Abram. "The reluctant imperialism of the medical profession." *Social science & medicine* 28, no. 11 (1989): 1165-1170.

Downing, Norman Lance, Joshua Rolnick, Sarah F. Poole, Evan Hall, Alexander J. Wessels, Paul Heidenreich, and Lisa Shieh. "Electronic health record-based clinical decision support alert for severe sepsis: a randomised evaluation." *BMJ quality & safety* 28, no. 9 (2019): 762-768.

Dyrda, Laura. 100 of the largest hospitals and health systems in America: 2019. Becker's Hospital Review. (2019).

Elish, Madeleine Clare, and danah boyd. "Situating methods in the magic of Big Data and AI." *Communication monographs* 85, no. 1 (2018): 57-80.

Elish, Madeleine Clare, and Tim Hwang. "Praise the Machine! Punish the Human! The contradictory history of accountability in automated aviation." SSRN (2015).

European Commission. "A definition of Artificial Intelligence: main capabilities and scientific disciplines." (2019): https://ec.europa.eu/digital-single-market/en/news/definition-artificial-intelligence-main-capabilities-and-scientific-disciplines

Evans, Laura. "A Closer Look at Sepsis-Associated Mortality." *JAMA network open* 2, no. 2 (2019): e187565-e187565.

Ferryman, Kadija, and Mikaela Pitcan. *Fairness in Precision Medicine*. (New York: Data & Society Research Institute, 2018.

Fleuren, Lucas M., Thomas LT Klausch, Charlotte L. Zwager, Linda J. Schoonmade, Tingjie Guo, Luca F. Roggeveen, Eleonora L. Swart et al. "Machine learning for the prediction of sepsis: a systematic review and meta-analysis of diagnostic test accuracy." *Intensive care medicine* (2020): 1-18.

Freidson, Eliot. *Profession of medicine: A study of the sociology of applied knowledge*. University of Chicago Press, 1988.

Futoma, Joseph, Sanjay Hariharan, and Katherine Heller. Learning to Detect Sepsis with a Multitask Gaussian Process RNN Classifier. *Proceedings of the 34th International Conference on Machine Learning*. Sydney, Australia, PMLR 70 (2017).

Futoma, Joseph, Sanjay Hariharan, Katherine Heller, Mark Sendak, Nathan Brajer, Meredith Clement, Armando Bedoya, and Cara Obrien. An Improved Multi-Output Gaussian Process RNN with Real-Time Validation for Early Sepsis Detection. *Proceedings of Machine Learning for Health care* 68 (August 2017), 1–12.

Gianfrancesco, Milena A., Suzanne Tamang, Jinoos Yazdany, and Gabriela Schmajuk. "Potential biases in machine learning algorithms using electronic health record data." *JAMA internal medicine* 178, no. 11 (2018): 1544-1547.

Glomb, Theresa M., John D. Kammeyer-Mueller, and Maria Rotundo. "Emotional labor demands and compensating wage differentials." *Journal of applied psychology* 89, no. 4 (2004): 700. doi:10.1037/0021-9010.89.4.700. PMID 15327355.

Greenhalgh, Trisha, Jeremy Howick, and Neal Maskrey. "Evidence based medicine: a movement in crisis?." *The BMJ* 348 (2014).

Hochschild, Arlie Russell. *The managed heart: Commercialization of human feeling*. University of California Press, 2012.

Houston, Lara. Steven J. Jackson, Daniela K. Rosner, Syed Ishtiaque Ahmed, Meg Young, and Laewoo Kang, "Values in Repair," *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*, ACM, (2016): 1403–1414, https://doi.org/10.1145/2858036.2858470.

"Improving the prevention, diagnosis and clinical management of sepsis." World Health Organization Report by the Secretariat. (2017).

Islam, Md Mohaimenul, Tahmina Nasrin, Bruno Andreas Walther, Chieh-Chen Wu, Hsuan-Chia Yang, and Yu-Chuan Li. "Prediction of sepsis patients using machine learning approach: a meta-analysis." *Computer methods and programs in biomedicine* 170 (2019): 1-9.

Jackson, Steven J. "Rethinking repair: breakdown, maintenance and repair in media and technology studies today." *Media meets technology*, MIT Press 68 (2013).

Kitchin, Rob. "Big data, new epistemologies and paradigm shifts." *Big data & society* 1, no. 1 (2014): 2053951714528481.

Leonelli, Sabina. "What difference does quantity make? On the epistemology of Big Data in biology." *Big data & society* 1, no. 1 (2014): 2053951714534395.

Lin, A.L. Mark Sendak, Armando D. Bedoya, Meredith E. Clement, Joseph Futoma, M. Nichols, M. Gao, Katherine A. Heller, Cara L. O'Brien. What Is Sepsis: Investigating the Heterogeneity of Patient Populations Captured by Different Sepsis Definitions. American Journal of Respiratory and Critical Care Medicine (2020); 201: A3299. doi:197:A3299.

Lin, A.L., Mark Sendak, Armando D. Bedoya, Meredith E. Clement, Nathan Brajer, Joseph Futoma, Hayden B. Bosworth, Katherine A. Heller, and Cara L. O'Brien. "Evaluating sepsis definitions for clinical decision support against a definition for epidemiological disease surveillance." bioRxiv (2019): 648907. doi: https://doi.org/10.1101/648907

Maiers, Claire. "Analytics in action: users and predictive data in the neonatal intensive care unit." *Information, Communication & Society* 20, no. 6 (2017): 915-929.

Mazmanian, Melissa, Ingrid Erickson, and Ellie Harmon. "Circumscribed time and porous time: Logics as a way of studying temporality." In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, pp. 1453-1464. 2015.

Miles, Matthew B., and A. Michael Huberman. *Qualitative data analysis: An expanded sourcebook*. sage, 1994.

Mitchell, Tom M. Machine Learning. (New York: McGraw Hill, 1997): p. 2. ISBN 978-0-07-042807-2.

Mittelstadt, Brent Daniel, and Luciano Floridi. "The ethics of big data: current and foreseeable issues in biomedical contexts." *Science and engineering ethics* 22, no. 2 (2016): 303-341.

Obermeyer, Ziad, Brian Powers, Christine Vogeli, and Sendhil Mullainathan. "Dissecting racial bias in an algorithm used to manage the health of populations." *Science* 366, no. 6464 (2019): 447-453.

Orlikowski, Wanda J., and JoAnne Yates. "It's about time: Temporal structuring in organizations." *Organization science* 13, no. 6 (2002): 684-700.

Pine, Kathleen H., and Max Liboiron. “The politics of measurement and action.” In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pp. 3147-3156. 2015.

Pine, Kathleen H., and Melissa Mazmanian. “Artful and contorted coordinating: The ramifications of imposing formal logics of task jurisdiction on situated practice.” *Academy of Management Journal* 60, no. 2 (2017): 720-742.

Pine, Kathleen H., and Melissa Mazmanian. “Institutional logics of the EMR and the problem of ‘perfect’ but inaccurate accounts.” In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*, 2014 pp. 283-294.

Procter, Rob, Joe Wherton, Trish Greenhalgh, Paul Sugarhood, Mark Rouncefield, and Sue Hinder. “Telecare call centre work and ageing in place.” *Computer Supported Cooperative Work* (CSCW) 25, no. 1 (2016): 79-105.

Rabin, R. C. “Could it be sepsis? CDC wants more people to ask.” *The New York Times*. (Sept 19, 2016). Available at: http://www. nytimes. com/2016/09/20/well/live/could-it-be-sepsis-cdc-wants-more-people-to-ask. html (2016).

Rhee, Chanu, Kathleen Chiotos, Sara E. Cosgrove, Emily L. Heil, Sameer S. Kadri, Andre C. Kalil, David N. Gilbert et al. “*Infectious Diseases Society of America Position Paper: Recommended Revisions to the National Severe Sepsis and Septic Shock Early Management Bundle (SEP-1) Sepsis Quality Measure.*” *Clinical Infectious Diseases* 2020. doi:10.1093/cid/ciaa059

Rhee, Chanu, Raymund Dantes, Lauren Epstein, David J. Murphy, Christopher W. Seymour, Theodore J. Iwashyna, Sameer S. Kadri et al. “Incidence and trends of sepsis in US hospitals using clinical vs claims data, 2009-2014.” *Jama* 318, no. 13 (2017): 1241-1249.

Rhee, Chanu, Michael Filbin, Anthony F. Massaro, Amy Bulger, Donna McEachern, Kathleen A. Tobin, Barrett Kitch et al. “Compliance with the national SEP-1 quality measure and association with sepsis outcomes: a multicenter retrospective cohort study.” *Critical care medicine* 46, no. 10 (2018): 1585.

Sachs, Sarah E. “The algorithm at work? Explanation and repair in the enactment of similarity in art data,” *Information, Communication & Society*, (2019): 1–17.

Sendak, Mark, Madeleine Clare Elish, Michael Gao, Joseph Futoma, William Ratliff, Marshall Nichols, Armando Bedoya, Suresh Balu, and Cara O’Brien. “The human body is a black box” supporting clinical decision-making with deep learning.” In P*roceedings of the 2020 ACM Conference on Fairness, Accountability, and Transparency*, pp. 99-109. (2020).

Seymour, Christopher W., Foster Gesten, Hallie C. Prescott, Marcus E. Friedrich, Theodore J. Iwashyna, Gary S. Phillips, Stanley Lemeshow, Tiffany Osborn, Kathleen M. Terry, and Mitchell M. Levy. “Time to treatment and mortality during mandated emergency care for sepsis.” *New England Journal of Medicine* 376, no. 23 (2017): 2235-2244.

Star, Susan Leigh, and Anselm Strauss. “Layers of silence, arenas of voice: The ecology of visible and invisible work.” *Computer supported cooperative work* (CSCW) 8, no. 1-2 (1999): 9-30.

Staunton, Orlaith. “The Rory Staunton Foundation for Sepsis Prevention.” *Huffington Pos*t. November 15, 2016.

Strauss, Anselm and Juliet Corbin. “Grounded theory methodology.” *Handbook of qualitative research* 17, no. 1 (1994): 273-285.

Strauss, Anselm, Shizuko Fagerhaugh, Barbara Suczek, and Carolyn Wiener. *Social Organization of Medical Work*. Chicago: University of Chicago Press, 1985.

Tan, Christelle, Kristin Corey, Mark Sendak, Michael Gao, Marshall Nichols, Mike Revoir, Armando Bedoya, Suresh Balu, Cara O'Brien. "Characterizing Sepsis Encounters Across Community and Quartnerary Hospitals Within an Academic Health System." Abstract published at Hospital Medicine. March 24-27, 2019. National Harbor, Md. Abstract 188.

Timmermans, Stefan, and Marc Berg. *The gold standard: the challenge of evidence-based medicine*. Temple University Press, 2010.

Trist, Eric. The evolution of sociotechnical systems. Occasional paper, (1981): 2

World Health Organization. "Improving the prevention, diagnosis and clinical management of sepsis." (April 13, 2017.) http://apps.who.int/gb/ebwha/pdf_files/WHA70/A70_13-en.pdf.

Yancy, Clyde W. "COVID-19 and African Americans." *Jama* (2020).

Yu, Kun-Hsing, and Isaac S. Kohane. "Framing the challenges of artificial intelligence in medicine." *BMJ quality & safety* 28, no. 3 (2019): 238-241.

DATA& SOCIETY

Data & Society is an independent nonprofit research institute that advances new frames for understanding the implications of data-centric and automated technology. We conduct research and build the field of actors to ensure that knowledge guides debate, decision-making, and technical choices.

www.datasociety.net
@datasociety
Illustrations by Yichi Liu

DATA & SOCIETY

www.datasociety.net

@datasociety