IMPROVING INTEROPERABILITY TO ADDRESS THE PHYSICIAN SHORTAGE

Applying Artificial Intelligence and Machine Learning to Improve Healthcare

TULSA INNOVATION LABS

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CENTER FOR
HEALTH SYSTEMS INNOVATION
OSU Center for Health Sciences

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The Center for Health Systems Innovation (CHSI), a joint venture between the Spears School of Business and the Center for Health Sciences at Oklahoma State University, established the Institute for Predictive Medicine (IPM) to tackle the physician shortage by leveraging AI and data analytics. The CHSI's mission is to transform rural and Native American health through implementing new delivery models and advanced Information Technology solutions.

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CONTENTS

Recommended Citation: Abdelmomin, S., & Miao, Z. (2021). Improving Interoperability to Address the Physician Shortage: Applying Artificial Intelligence and Machine Learning to Improve Healthcare. Tulsa: Tulsa Innovation Labs.

INTRODUCTION

Alleviating the current primary care physician shortage would save 7,000 American lives annually[1]. Unfortunately, the U.S. demand for physicians in every specialty has outpaced supply since 2018, and this deficit is expected to worsen over the next few years[2]. In December 2020, Congress took a step toward addressing the physician shortage by adding 1,000 new Medicare-funded Graduate Medical Education spots, the first increase in the number of federally appointed residency spots since 1997. Despite this effort, studies still show that our country will experience a severe physician shortage. As a result, the medical community is now looking to health data technologies for solutions. Today, most health data capture is driven by billing purposes. However, ballooning healthcare demand and the precipitous physician shortage are forcing healthcare systems to turn to data-driven solutions such as Artificial Intelligence (AI) and Machine Learning (ML) for help. Realizing AI/ML's potential to improve workflow efficiency and physician satisfaction, healthcare systems are starting to think of ways to enhance interoperability — or timely health data collection, exchange and use.

This report synthesizes and analyzes insight from health data experts, physician interviews and primary literature to explore how data-driven technologies can help alleviate the effects of the physician shortage. To navigate this complex challenge, the report will discuss:

1. The Causes and Effects of the Physician Shortage
2. AI, ML, DL Alphabet Soup: What Does It Mean and How Can It Help?
3. Examples of How AI Can Reduce Physician Burnout and Critical Care Overload
4. Navigating Barriers To Widespread Adoption of Health AI Technologies

Additionally, the report includes a project spotlight that provides a peek into the future of health AI/ML technologies.

THE CAUSE AND EFFECTS OF THE PHYSICIAN SHORTAGE

According to the Association of American Medical Colleges (AAMC), this deficit is expected to grow between 37,800 and 124,000 physicians by 2032[2]. Although this estimate reflects the total national physician deficit, it does not reflect the variable severity of the shortage across different states. A study from the Cleveland Clinic Lerner College of Medicine and the Veteran's Affairs Office of Rehabilitation Research & Development Service supports the AAMC's shortage estimates. This study highlights how highly populated western and southern states such as California, Florida, and Texas will experience the most severe shortages. In addition, states with large rural populations will experience a moderate but

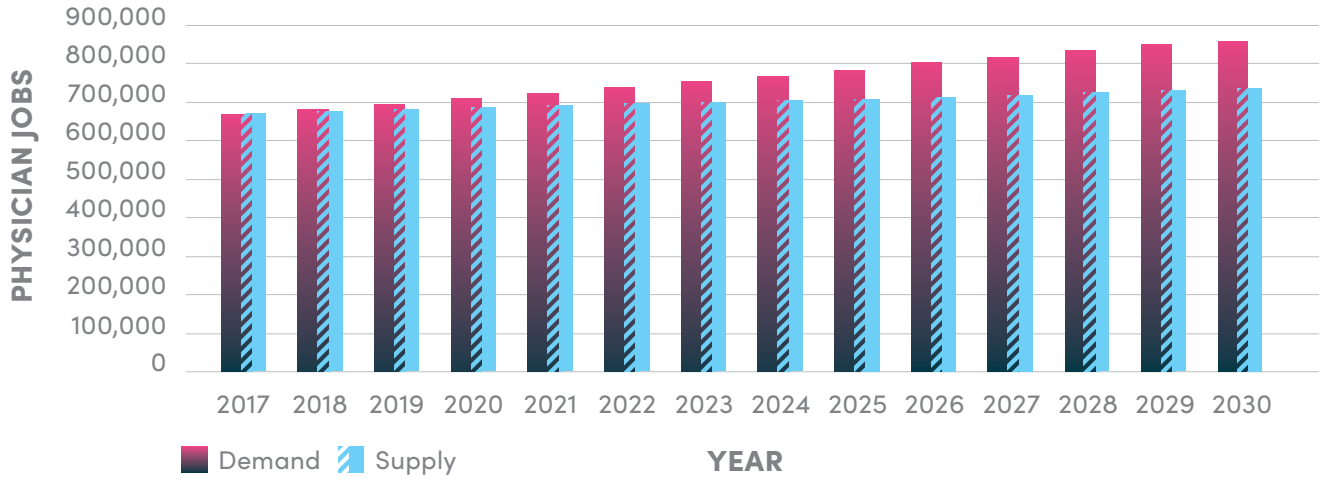
significant physician shortage. For example, 30 out of the 77 counties in Oklahoma have 10 or fewer physicians, and many states will face a similar fate within the next few years[3]. In contrast, northeastern states like New York, Massachusetts and Connecticut will experience a modest physician surplus by 2030[4]. Nonetheless, most states will face a physician shortage, so improving physician workflow efficiency and retention to best use the physicians available will be vital to navigating this health crisis.

40% of active physicians will reach retirement age by 2030

The nation's growing elderly population increases the demand for physicians faster than medical schools can produce doctors[1]. Additionally, the medical field contends with rising burnout rates caused by severe clinician exhaustion and stress. Burnout triggers physicians' early retirement, career switches and poor mental health. Each of these factors hacks away at the desperately needed pool of active physicians[1]. The effect of the unmet physician demand is clinical care overload (CCO), a state in which clinical systems cannot adequately treat the volume of patients they receive, leading to delayed medical care and poor patient outcomes.

The projected U.S. population growth rate is 10.4% within the next 15 years[5]. However, the over-65 population will increase by 45.1% in that same time frame[3]. As the over-65 population grows, so does the need to manage complex chronic health conditions such as cardiovascular disease and diabetes, increasing the demand for physicians. Additionally, as the population ages, so do our doctors. AAMC's study also found that 40% of active doctors will be over 65 by 2030[1]. The supply gap created by the aging population is especially stark when looking at the field of cardiology. Today, nearly half of all Americans have a form of cardiovascular disease, and that statistic will only rise with the aging population[6]. That percentage becomes concerning when juxtaposed with the fact that 62.8% of active cardiologists will reach retirement age over the next decade[7].

PROJECTED PHYSICIAN DEMAND AND SUPPLY FROM 2017 TO 2030 IN THE UNITED STATES[1]



Source: L Zhang, X., Lin, D., Pforsich, H., & Lin, V. W. (2020). Physician workforce in the United States of America: forecasting nationwide shortages. Human resources for health, 18(1), 8. https://doi.org/10.1186/s12960-020-0448-3

In addition to the aging patient and physician population, rising physician burnout is exacerbating the physician shortage[1]. One factor contributing to the increase in burnout is the growth of non-clinical physician responsibilities. Physician administrative responsibilities such as the upkeep of electronic health records (EHRs) in hospitals, were the products of value-based initiatives, but they have forced doctors into both caregiver and clerical roles. Documentation and reporting demands cause physicians to spend upwards of 50% of their time on administrative work, forcing them to have fewer and less-focused patient interactions, less job satisfaction and higher reported stress levels[8]. Job dissatisfaction and burnout correlate to rising physician suicide rates, career changes and early retirement amongst physicians[4]. Medscape's 2021 Annual Report revealed that 10% of physicians experiencing burnout consider leaving medicine[4]. This statistic proves especially significant when considering that upwards of 50% of physicians report at least one symptom of burnout[4]. Even more disturbing, a 2018 meta-analysis on physician burnout found that the suicide rate is 2.27 times higher among female physicians than the general female population and 1.41 times higher among male physicians than the general male population[9]. These statistics highlight the desperate need to improve physician-job satisfaction and retention.

The increase in physician demand created by the growing elderly population and the decrease in physician supply due to excessive burnout rates create a lag in the healthcare delivery system known as clinical care overload. During COVID-19, there was an exaggerated form of CCO when hospitals struggled to find equipment and manpower to treat critically ill patients. Even before the pandemic, CCO manifested in long emergency room wait times and late interventions for time-sensitive conditions such as stroke and heart attacks. This bottleneck in care delivery can be addressed by improving workflow inefficiencies.

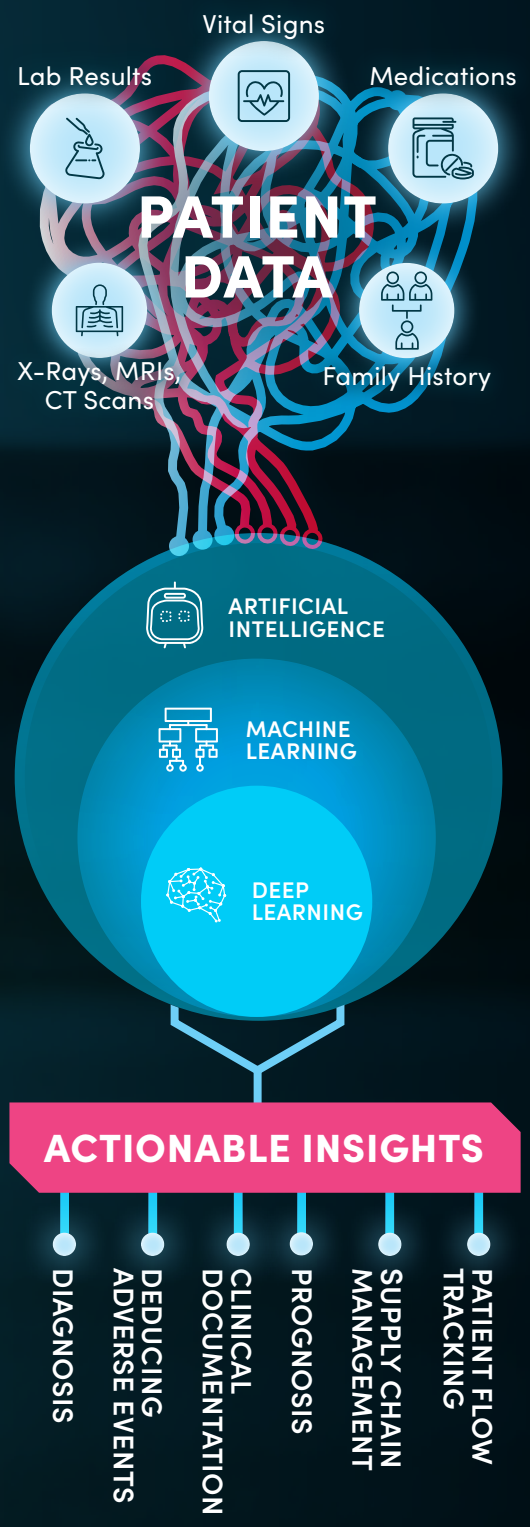
Automating inefficient workflow models is one of the ways AI can lower the burden of the physician shortage. The following sections will highlight current AI use cases that resolve time-consuming administrative tasks and inefficient workflows to reduce burnout, CCO and, in turn, the burden of the physician shortage.

AI, ML, DL ALPHABET SOUP:
WHAT DOES IT MEAN AND HOW CAN IT HELP?

Before discussing how AI solutions can ease the burden of the physician shortage, it is essential to understand how AI and its subfields are defined. Artificial Intelligence (AI) is any technological solution that perceives data input and uses that input to generate an increasingly accurate response. AI is the umbrella term that houses Machine Learning (ML) and Deep Learning (DL) as subsets, but AI can also be understood as the simplest type of data-driven technology. Autonomous vacuums are one example of AI because they use simple if-then algorithms to avoid crashing into walls. This algorithm might look like, "if sense wall, then turn left."

ML is a subset of AI that uses statistical methods to improve its probability of success. Visualize an ML model as an impressive decision tree with probabilities at each branch. ML models adjust the branch probabilities when they receive additional data and become more accurate due to this self-correcting process. This process is also why larger datasets train models to be more accurate. For example, people use ML on their navigation apps to find the fastest route from point A to B. The map app's ML model constantly picks up movement data from other cars along all possible routes to adjust branch probabilities to predict the fastest path to point B.

DL models are a step up in complexity from ML models, as they stack multiple algorithms into layers that create an artificial neural network that can learn and make intelligent decisions on its own. Unlike ML models, DL models are so complex that data scientists cannot trace back a decision tree to understand the logic behind why DL models make decisions. For this reason, DL models are considered black boxes.



Predictive Analytics (PA) and Natural Language Processing (NLP) are AI applications that can use ML or DL models and are commonly used in the healthcare setting. PA is a specific type of AI that uses current and historical data to predict future outcomes. NLP is AI that embeds linguistic rules into algorithms to create technologies that can read and understand human language.

Health AI technology can decrease clinical overcrowding and physician burnout by reducing EHR burden, making diagnosis and prognosis predictions, managing supply chains and patient flow and analyzing patient data to create precision medicine treatments.

The rest of this paper will explore how current data technologies can reduce the effects of the physician shortage by mitigating workflow inefficiencies that contribute to burnout and clinical overload, the current barriers to adopting and developing these solutions and what the future holds for the intersection of data analytics and healthcare.

COMBATING PHYSICIAN BURNOUT

STREAMLINING ADMINISTRATIVE TASKS

Electronic Health Records (EHRs) were widely adopted in the early 2010s after the American Recovery and Reinvestment Act of 2009 (ARRA) authorized incentive payments to eligible hospitals and physicians that are "meaningful users" of electronic health records[6]. The U.S. federal government supported this adoption to encourage physicians to keep precise records about medical conditions, standardize clinical treatment and improve treatment quality[10].

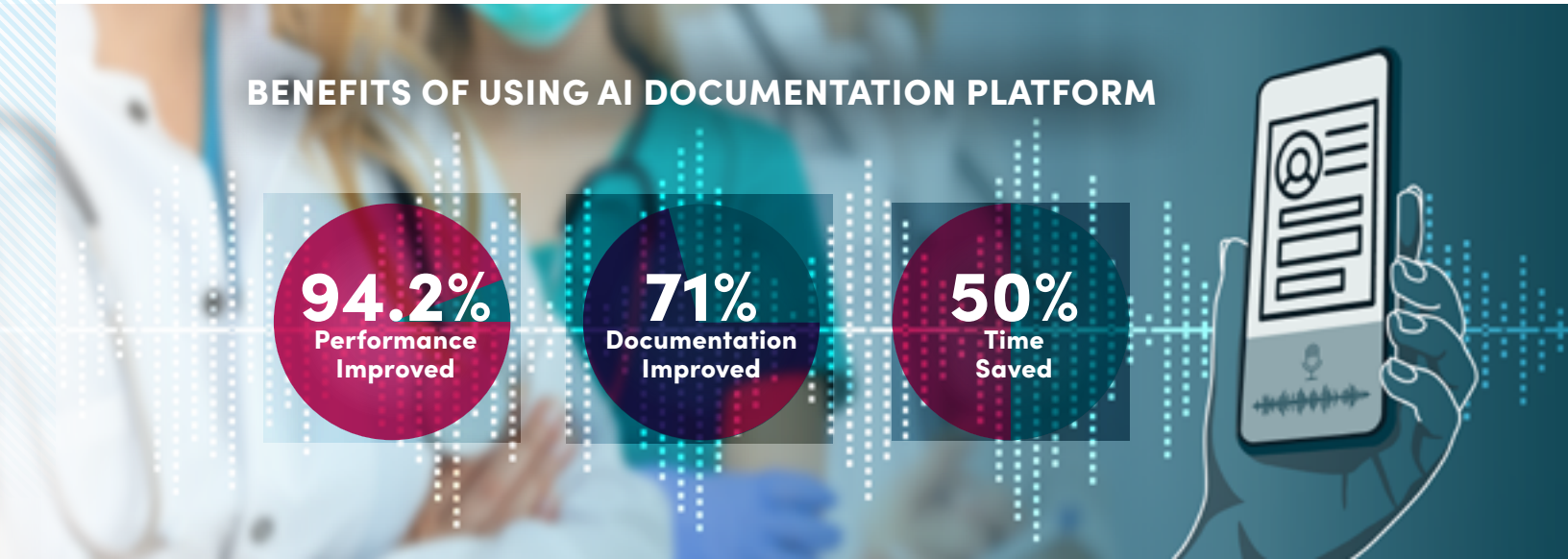
However, demand for healthcare records and patient data creates a substantial burden on healthcare providers. Doctors spend an average of 16 minutes charting and recording notes per patient visit[2], nearly equivalent to the 18 minutes spent with each patient[11]. Unsurprisingly, logging information in EHRs is a task many physicians find mentally and emotionally draining because it detracts from the time for the doctor-patient interaction. The excessive demand for charting is one of the highest reported factors for physician burnout[5].

Since the adoption of EHRs, many clinical and industry stakeholders have tried to create solutions to reduce medical documentation burden and improve physician satisfaction. The most significant development in EHR optimization occurred with the maturity of speech recognition software. However, voice recognition alone cannot sort the dictated information into the appropriate fields, such as prescription orders, pulse and blood pressure, but NLP techniques can analyze and sort the dictated medical notes into usable data fields.

Nuance's Dragon Medical Virtual Assistant is making strides to accomplish seamless EHR functions using their AI solutions. The Dragon Medical Virtual Assistant is a software product that offers three solutions: Dragon Medical One, the voice recognition platform, and Dragon Medical Advisor, which provides real-time suggestions to ensure the accuracy of medical notes and the differential diagnosis process. The third solution in the bundle is the PowerMic Mobile, which turns the physician's smartphone into a secure wireless microphone that allows physicians to use the platform on the go.

A study at Nebraska Medical surveyed 350 physicians who used Dragon Medical. Nuance's AI documentation platform reduced physician documentation time and improved documentation quality. It showed that 94.2% of physicians indicated that Nuance's AI tool helped them do their job better[12]. Additionally, 71% of respondents reported that documentation quality improved, and 50% said they reported saving at least 30 minutes a day using Dragon Medical[8].

As the use and familiarity of users of data-driven tools increase, workflow efficiency improves as well. Simultaneously, the AI model continues to refine itself to become more accurate in its speech detection and prediction capabilities. This improvement process takes time and data input and healthcare systems



cannot afford to expose patients to the risk of a learning mistake (e.g., inaccurate transcribing of a medication order). This AI learning curve highlights the need for easily accessible and anonymous healthcare data that can be used to train these models safely. The auto-refinement capabilities will only increase the accuracy and efficiency of health data documentation, reduce administrative burden and improve physician satisfaction and retention. However, if health systems neglect to create the data-sharing conditions needed to safely train these models, the development and adoption of tools will be unnecessarily slow and costly.

EFFECTIVE AND EFFICIENT CLINICAL DECISION MAKING

> **"Most of us [physicians] are using predictive analytics, even if we don't realize that's what we're using. We use it primarily to predict risk for heart attack, and there are quite a few different settings in which we're predicting people's future risk for cardiac disease ... diagnoses that took us six months to figure out, maybe we can figure out in a week with predictive analytics."**
>
> **Dr. Scott Shepherd**
> Medical Director, OSU Center for Health Systems Innovation

As mentioned previously, time-consuming administrative tasks such as health documentation and reporting have limited critical patient-physician time. Physicians find fulfillment in their careers primarily from delivering patient care. As patient interaction decreases, so does job satisfaction, exposing the physician to long periods of emotional exhaustion that can result in burnout. One way to increase face-to-face patient time is by streamlining their clinical decision-making processes with predictive analytics AI.

Many AI technologies have been developed to make clinical decisions more accurate and efficient. Dr. Scott Shepherd, Medical Director, OSU Center for Health Systems Innovation, explained, "Most of us [physicians] are using predictive analytics, even if we don't realize that's what we're using. We use it primarily to predict risk for heart attack, and there are quite a few different settings in which we're predicting people's future risk for cardiac disease."

Time is the most critical factor in successfully treating cardiac arrest. Therefore, using predictive analytics to calculate a patient's probability of cardiac arrest and estimating onset time is at the forefront of the medical community's concern. A study out of Tarbiat Modares University in Tehran used a dataset of 40,000 patients from Beth Israel Deaconess Medical Center to create a prognostic model that predicts cardiac arrest in sepsis patients hours before the event.

The study's primary investigators, Dr. Javan and Dr. Sepehri, stacked several traditional algorithms to create a new model that accurately predicted 85% of cardiac arrest cases one hour before the incident and 73% of arrest cases 25 hours before the event[13]. This highly effective model has yet to be used in clinical settings, but it provides a hopeful future for how healthcare systems can treat the number one cause of death in the United States[14].

Using AI to move clinical management from reactive to proactive clinical decision-making will help physicians make more efficient and accurate treatment plans that expedite the diagnosis process. This approach will result in higher physician satisfaction while improving patient health outcomes.

In palliative care, other cases have utilized proactive clinical decision-making to reduce time and unnecessary resources. Palliative care is end-of-life management used by hospitals to improve end-of-life quality and decrease costs. According

to the Center to Advance Palliative Care, patients who receive palliative care spend 43% fewer days in the hospital and 33% fewer days in the ICU[15]. Additionally, palliative care was estimated to save healthcare systems between $7,000 and $8,000 per patient compared to usual acute care treatment[16]. However, patients rarely receive a palliative care specialist referral because determining when to begin palliative care is not always clear.

Many patients spend weeks, months or even years receiving invasive hospital interventions before the physician decides to pursue palliative care. In a TIL interview, Dr. Shepherd shared, "... diagnoses that took us six months to figure out, maybe we [physicians] can figure out in a week with predictive analytics." These clinical decisions have traditionally been highly subjective, but AI models can scan millions of data points to recommend an objective and reliable treatment plan. In the time it takes the clinician to make this difficult decision, the hospital is expending valuable resources that do not improve the patient's condition. The compounding effect of multiple patients simultaneously using finite critical care resources results in unnecessarily high demand for ICU physicians, which creates a bottleneck in care delivery that leads to poorer patient outcomes.

Palliative Connect, a predictive analytics software created at the University of Pennsylvania Perelman School of Medicine, is a predictive AI model that assesses the patient's condition to generate a prognosis score that helps physicians determine the patient's most likely outcome over the next six months. In a HealthTech Magazine interview, Katherine Courtright, Assistant Professor of Medicine at the Perelman School of Medicine, explained that the software works by "identifying patients who are at the highest risk of a bad outcome when they come into the hospital," which allows physicians to recommend palliative care treatment proactively[17]. In a pilot at one of Penn Medicine's hospitals, the program increased palliative care consultations by 74%[18]. By using these data-driven insights, physicians can more efficiently provide care, reduce resource waste and improve the patient's end-of-life outcomes. In aggregate, adopting solutions like Palliative Connect can improve healthcare efficiencies and patient engagement to help reduce physician burnout.

REDUCING CLINICAL CARE OVERLOAD

PREVENTATIVE MEDICINE

> "A lot of what we [physicians] do is reactionary, but predictive analytics presents the opportunity to be more ahead of the game than we are typically right now."
>
> **Dr. Lance Black**
> U.S. Air Force Physician and Medical Technology Development Specialist

AI models can stratify at-risk patients to help clinics and hospitals allocate resources more effectively and allow for upstream intervention. "A lot of what we [physicians] do is reactionary, but predictive analytics presents the opportunity to be more ahead of the game than we are typically right now," explained Dr. Lance Black, a family medicine physician, medical technology development specialist and Senior Medical Director at 3ive Labs. Upstream interventions spread out clinical care demand by lowering the number of high-acuity patients that require resource-intensive treatments. Preventative medicine is key to diminishing the most debilitating consequence of the physician shortage, clinical care overload (CCO). CCO refers to the congestion experienced in clinical settings due to spikes in patient volume and the finite nature of medical resources such as healthcare staff and equipment. Using PA to create preventative solutions is one way to keep patient surges and CCO to a minimum.

Preventative AI models use demographic and medical history records at both the individual patient and population levels to make predictions about an individual's prognosis. Using PA to suppress patient surges benefit both the physician and the patient. From the patient's perspective, preventative measures mean shorter wait times, faster care delivery and better health outcomes. From the physician's perspective, doctors can feel comfortable spending more time with their sickest patients who desperately need additional medical resources without being overwhelmed. Preventative AI optimizes the physician's caseload. This can then improve quality patient-physician interactions, decrease physician burnout and, hopefully, increase physician retention.

One great example of preventative medicine keeping patient volume and acuity low is the predictive retinopathy tools created at the Institute for Predictive Medicine (IPM) at Oklahoma State University Center for Health Systems Innovation (CHSI). Diabetic retinopathy (DR) is a leading cause of blindness among working-age adults. DR can progress to irreversible stages where it is impossible to restore the patient's sight. Therefore, early detection and treatment are essential in preventing DR and subsequent vision loss. By analyzing thousands of de-identified health data records, the CHSI has identified 10 critical indicators in DR progression. They used these indicators to develop an AI model that has greater than 80% accuracy for DR prognosis[19]. This predictive technology is noninvasive, inexpensive and able to provide effective early warnings that keep patients from needing complex and costly care down the road. Using preventative data tools such as this mediate downstream patient volume surges and improve patient outcomes.

REDUCING READMISSION

The AI model was **74.22%** to **75.41%** **ACCURATE** at predicting patient readmissions.

Another way PA can be used to manage downstream patient volume and CCO is through readmission rate reduction. According to the Center for Health Information Analysis, roughly 2 million patients are readmitted to hospitals each year[20]. These readmissions cost Medicare $27 billion in medical services and equipment each year[12]. This analysis found that $17 billion of readmission costs are avoidable[12]. The highest rate of readmission occurs among chronic disease patients within 30 days of their initial discharge date[21]. The lab of Dr. Dursun Delen at OSU CHSI has created a model that predicts the risk of readmission for patients who suffer from heart failure and chronic obstructive pulmonary disease (COPD). The model used a dataset of 32,350 unique heart failure patients and a second dataset of 31,070 unique COPD patients[22]. Using those anonymized patient records, Dr. Delen's lab created two models that predict a patient's risk for readmission with a performance rating (also known as a ROC AUC[i]) of 74.22 to 75.41%, indicating the reliable accuracy of the model[18,23]. The development and adoption of this AI tool will allow healthcare systems to deploy readmission-reducing measures such as at-home follow-ups, remote monitoring and rehabilitation programs such as cardiopulmonary rehab and physical therapy. Using AI to guide preventative treatments will allow physicians to get ahead of avoidable CCO, so healthcare systems must expedite the adoption of these solutions.

[i]ROC AUC, receiver operating characteristic area under the curve, is a standard performance measurement that evaluates sensitivity and specificity of AI and machine learning models. A ROC score of 0.5 indicates no discrimination, and scores above 0.7 indicated acceptable discrimination for AL/ML models.

NAVIGATING BARRIERS TO WIDESPREAD ADOPTION OF HEALTH AI TECHNOLOGIES

From Siri and Alexa to navigation apps and your email spam filter, AI is everywhere. The abundance of data on the internet had made AI ubiquitous. However, there are still barriers that prevent widespread adoption of AI across healthcare systems in the U.S. Some of the biggest barriers to health data technology advancement and adoption include:

- Variable, Incomplete, and Unrepresentative Datasets
- Culture and Skepticism
- Ambiguous ROI Validation

VARIABLE, INCOMPLETE AND UNREPRESENTATIVE DATA

Any discussion on the barriers to implementing AI technologies would be incomplete without addressing the quality of the datasets used to create these models. Accessing representative, structured and usable health data is extremely difficult. First, accessing data that provide an accurate model of individual patients and a patient population is difficult because patient data is fragmented across many healthcare systems and is incomplete due to human error during the data collection process. Additionally, many current datasets are unrepresentative of medically underserved populations, which introduces the potential for bias to be propagated in any model developed from these datasets. Moreover, the raw information that medical staff inputs into data systems is variable because there are no universally accepted health data coding and input standards. The variability of the data makes it difficult for AI models to recognize the data point. These unrecognizable data points are called unstructured data and are unusable. To make these data usable, a human manually labels or cleans the data. Data interoperability standards such as HL7® FHIR® could systematize health data collection and save valuable time and money in data labeling services, but these data collection guides have yet to achieve widespread adoption. To resolve these data quality obstacles, it is imperative to create regional data hubs that pool patient data from their respective populations that appropriately represent the region's racial, socioeconomic, geographic, gender and disease diversity. In other words, the data must accurately represent the people it intends to serve.

> **"Those who don't seek out care and those who don't have access to care are underrepresented in the databases. They are typically only seen in the databases as inpatient visits and emergency room visits so they're not represented."**
>
> **Dr. Scott Shepherd**
> Medical Director, OSU Center for Health Systems Innovation

Achieving representative datasets starts with how and where that data collection occurs. Dr. Shepherd explained, "Those who don't seek out care and those who don't have access to care are underrepresented in the databases. They are typically only seen in the databases as inpatient visits and emergency room visits so they're not represented." The AI tools created from these datasets

fail medically underserved populations such as low-income, rural, Black and Brown communities[24]. Universities, hospitals and clinics are the predominant health data collectors, so data scientists and developers must recognize the populations that are traditionally underserved by these systems and account for the lack of representation in their data. Improving data collection processes and providing disclaimers on who can safely use data tools is key to developing and adopting beneficial health AI tools.

Recently, private hospital systems and research institutions have done a better job of amassing enough data to build a patient population model for a specific disease interest. Unfortunately, that data is not inclusive of a patient's full contextualized history because research projects that lead health data collection are narrowly focused on a single area of study or pathology. The risk to patients comes into play when narrowly focused data collection processes result in scientific conclusions and interventions that are extrapolated to larger and more complex populations. Health Information Exchange (HIE) systems have attempted to unify patient data silos and create longitudinal health records to improve patient care and lower healthcare costs. Unfortunately, most HIE systems have failed due to unsupportive state-government policies and outdated data exchange methods such as faxing and mail. Furthermore, most state HIEs have yet to experiment with de-identifying their data to realize their external innovation capabilities.

Creating datasets that are representative of a large heterogeneous population is difficult, and getting a complete picture of a single patient is just as challenging. Rock Health President Tom Cassels explained that adequate and representative models need "longitudinal records rather than transactional systems" to improve the accuracy and applicability of AI tools like predictive analytics models. A patient's health data is scattered across all the clinics, hospitals and family offices they have visited in their lifetime. Not only does this fragmentation limit the physician's ability to care for the patient, but it also makes it nearly impossible to get a complete patient model needed to create accurate and precise health AI solutions.

> **"Adequate and representative models need longitudinal records rather than transactional systems to improve the accuracy and applicability of AI tools like predictive analytics."**
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> **Tom Cassels**
> Rock Health President

Even when demographically representative datasets are collected, the parameters fed into the model may still lead to the automation of racial discrimination in healthcare. In a study that investigated the racial bias in a widely used commercial triage algorithm, Dr. Ziad Obermeyer and his lab at the University of California, Berkeley found that the AI model underestimated the healthcare needs of Black patients[24]. This error was caused by the parameter used to approximate need — cost. Unequal access to care means healthcare systems spend less money caring for Black patients than for White patients. For this reason, the model that used cost as a proxy for need automatically underestimated the care required for Black patients in that healthcare system[25]. Obermeyer and his team recalibrated

the model's parameters by extracting and cleaning the EHR data to parse the severity of each case as opposed to just the number of illnesses presented. Once the model was updated, the number of Black patients eligible for intervention doubled. This oversight underscores the need for medical ethicists and diversity specialists to be involved in the development of health data repositories.

Once a large and representative dataset has been compiled, data labeling must occur to enable the readability and usability of the data. Most EHR datasets are a mess of structured and unstructured, often indiscernible, data points. These data must be labeled so that a technological model can understand the significance of an X-ray, biopsy scan or vital sign values. For example, in the Obermeyer study, the dataset was not changed, but effort was put into labeling the existing data so that the model could recognize data points that conveyed the severity of the patient's illness. Historically, this required hours of manual labor labeling medical notes and scans to feed into models. Today, health Data Curation as a Service (DCaaS) businesses like Verinovum are cutting down the cost and labor demand of data cleaning. Verinovum, a health DCaaS company based in Tulsa, Oklahoma, has improved case targeted data usability for its customers from 14% to 89% by cleansing, curating and enriching data from hundreds of contributing sources. Adopting health-specific DCaaS can lead to more accurate and precise models, so if state and regional healthcare systems wish to lead the health data industry and improve patient outcomes, they must create partnerships between their health data systems and DCaaS companies.

DECENTRALIZED AND FRAGMENTED HEALTH DATA

Difficulties with implementing Predictive Analytics:

1. Patient data is scattered across siloed healthcare facilities
2. Current datasets poorly represent medically underserved populations
3. Health data input is nonuniform, unstructured and unrecognizable to AI models

CULTURE AND SKEPTICISM

Although healthcare systems are eager to adopt AI solutions, one of the most pronounced barriers is skepticism from healthcare workers. While clinicians and scientists are comfortable with routine statistical tests, performance metrics used to evaluate the myriad of ML tools are often foreign. Moreover, the tools themselves are frequently black-box algorithms that cannot be fully dissected and deconstructed, even by experts.

Skepticism toward data-based technology also comes from the lack of transparency and privacy protection for the patients whose data is used by these tools. As mentioned in the representation discussion, datasets that feed AI models need an accurate representation of the patients it will treat. Until health data representativeness is improved, health AI companies and physicians will need to be transparent about the technology's limitations. For example, if the origin of the data cannot be traced, both the physician and the patient are in the dark as to how effective or potentially harmful the tool can be. Thus, there is a need for health data governance and standards that provide clear patient data guidelines and use-case limitations to minimize patient harm. But beyond external governing bodies, AI models need authorization checkpoints and model accuracy feedback to allow operators and healthcare workers to double-check the validity of the AI output. Building ML checkpoints into AI is relatively new but, in the future, bias and accuracy checkpoints and notifications will be standard practices that will increase healthcare workers' trust and comfortability with AI.

AMBIGUOUS ROI VALIDATION

> "Labor replacement cost is really hard to calculate. What is 30% of nurses' time? Hospitals still pay that nurse the same salary, so finding a way to justify the upfront cost of adoption is something health AI companies need to figure out, and it is very challenging."
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> **Dr. Lance Black**
> U.S. Air Force Physician and Medical Technology Development Specialist

Accenture analysts made headlines when they announced that health AI applications will produce $150 billion in annual savings for the United States healthcare economy by 2026[27]. However, real-world return on investment (ROI) for healthcare systems is much more ambiguous to prove. Today, most health data startups frame their solutions' ROI as a percent of time saved from an employee's workweek. While this rationale demonstrates efficiency improvements, it falls short of demonstrating the bottom-line that healthcare executives need to justify the risk and cost of the tool. As Dr. Black explained, "Labor replacement cost is really hard to calculate. What is 30% of nurses' time? Hospitals still pay that nurse the same salary, so finding a way to justify the upfront cost of adoption is something health AI companies need to figure out, and it is very challenging."

One approach to overcome this barrier involves comparing the new solution to existing standard of care practices and devices. The issue with this tactic is that many health AI solutions have no comparable solutions in existence. Another approach achieving ROI demonstration is to create AI solutions that target federally incentivized benchmarks such as readmission rates and patient satisfaction rating for which the Centers for Medicare & Medicaid Services (CMS) provides monetary bonuses to eligible clinical systems. The concern with this method is that the scope of data solutions becomes too narrowly focused, excluding innovations that address operational inefficiencies. Startups must always ask themselves, "What problem is this solving, and who will want to pay for it?" when designing AI solutions. Otherwise, they will have a hard time breaking into a hospital system.

SOLUTIONS

The single most important step to improving interoperability and health AI development is consensus. The technological components needed to create world-class interoperability systems currently exist, but consensus and trust between various health data silos are needed to utilize these technologies. Healthcare providers, AI companies, regional governments and payors need to achieve consensus on how to govern, regulate and label health data and AI technologies to expedite the development of AI solutions needed to address the physician shortage. Currently, health systems address each of these barriers individually. However, fragmented execution will likely be a decades-long endeavor, putting resolution outside of a relevant time frame to address the physician shortage.

The second approach to improving interoperability aims to achieve consensus to create a region-wide health data repository with health information exchange (HIE), government, industry and academic partners. This collaborative approach will streamline the individual implementing step mentioned above. Creating partnerships that include government, academic and private collaboration would help create uniform transparency, patient data protection and training guidelines while expediting data-tech innovation, development and adoption. This model would also promote widespread data collection and curation that would, in turn, create datasets that accurately represent the region of interest, which would reduce bias in AI models. Although a region-wide health data repository will not solve the ROI validation dilemma, it will reduce the cost of development and testing to decrease the risk and upfront cost associated with adopting a health AI tool. Overall, city- and state-wide repositories have the potential to turn their regions into health data meccas by collaborating to expedite the implementing step to health data tool research, innovation and adoption.

One case study of health data centralization is the Delaware Health Information Network (DHIN). The nation's first state HIE, DHIN, launched in 2007, and by 2012, it enrolled 86% of Delaware health providers and became financially sustainable[28]. Today, DHIN has enrolled over 96% of care providers in the state, equating to 2.9 million unique patient profiles, making it one of the largest health data exchange platforms in the country[22]. DHIN is financially sustainable because it uses its health data to create and sell health AI services to hospitals in its network. The HIE sells services such as the Encounter Notification System (ENS), which delivers real-time alerts of a patient being admitted, transferred or discharged from a DHIN participating hospital. Not only does this health data exchange system improve care delivery by giving physicians a complete picture of the patient history, but it also gives health data access and control back to the patient through their Health Check Connect system. Delaware's success is accredited to its small size and state-wide support of one HIE as opposed to many small competing HIEs. Delaware only has three major health systems, and the HIE received early support and guidance from state government. These two conditions facilitated rapid and unified adoption of robust HIEs, and other states have taken advantage of these characteristics. Nebraska's CyncHealth, Colorado's CORHIO and Arizona's Health Current all have thriving HIEs because they benefited from their small size and early state government support.

Although Delaware has done a fantastic job centralizing its health data and internally innovating, it has yet to take steps toward promoting external health AI innovation in the state. Oklahoma's HIE, MyHealth Access Network, is one of the first HIE systems to directly engage local innovators and mature independent health data solutions. For example, in 2013, Verinovum, the DCaaS company mentioned earlier, built their initial minimum viable product in support of MyHealth needs. The relationship eventually expanded into a multi-year enterprise arrangement wherein Verinovum provided critical data processing and infrastructure cleansing to support MyHealth's community quality measurement and intervention goals. MyHealth Access Network aims to expand its internal and external innovation capabilities to spur the developments of health data solutions and companies such as Verinovum and position Tulsa, Oklahoma, as one of the country's top health AI innovation hubs.

> **"The most important asset health information exchanges have is actually not the data, it's the trust that the healthcare community puts in us [HIEs] to hold their data."**
>
> **Dr. David Kendrick**
> CEO of MyHealth Access Network

Oklahoma is not the only area that hopes to lead the country into the anticipated AI golden age. Health AI-focused incubators and accelerators like AI Nexus Lab, DataRobot and Amazon's Alexa Accelerator have become more popular in recent years. This trend is expected to grow alongside the health AI industry, which is projected to reach a value of $120.2 billion by 2028[29]. The biggest value add these incubators offer data entrepreneurs is access to health data and connections to potential customers — two assets every HIE has at its disposal. Dr. David Kendrick, CEO of MyHealth Access Network, explained, "The most important asset health information exchanges have is actually not the data, it's the trust that the healthcare community puts in us [HIEs] to hold their data." This unique relationship between the HIEs and healthcare providers perfectly positions HIEs to be health AI technology funnels that facilitate health AI adoption. Such relationships and introductions would streamline the adoption process and spur rapid growth within the health AI industry. Although there are no HIE-affiliated AI incubators yet, as legal and incentive structures are defined, expect top HIE states like New York, Oklahoma, Delaware and Nebraska to stand up similar programs within the next decade.

WHAT'S NEXT: THE FUTURE OF CLINICAL CARE AND AI HEALTHCARE WORKERS

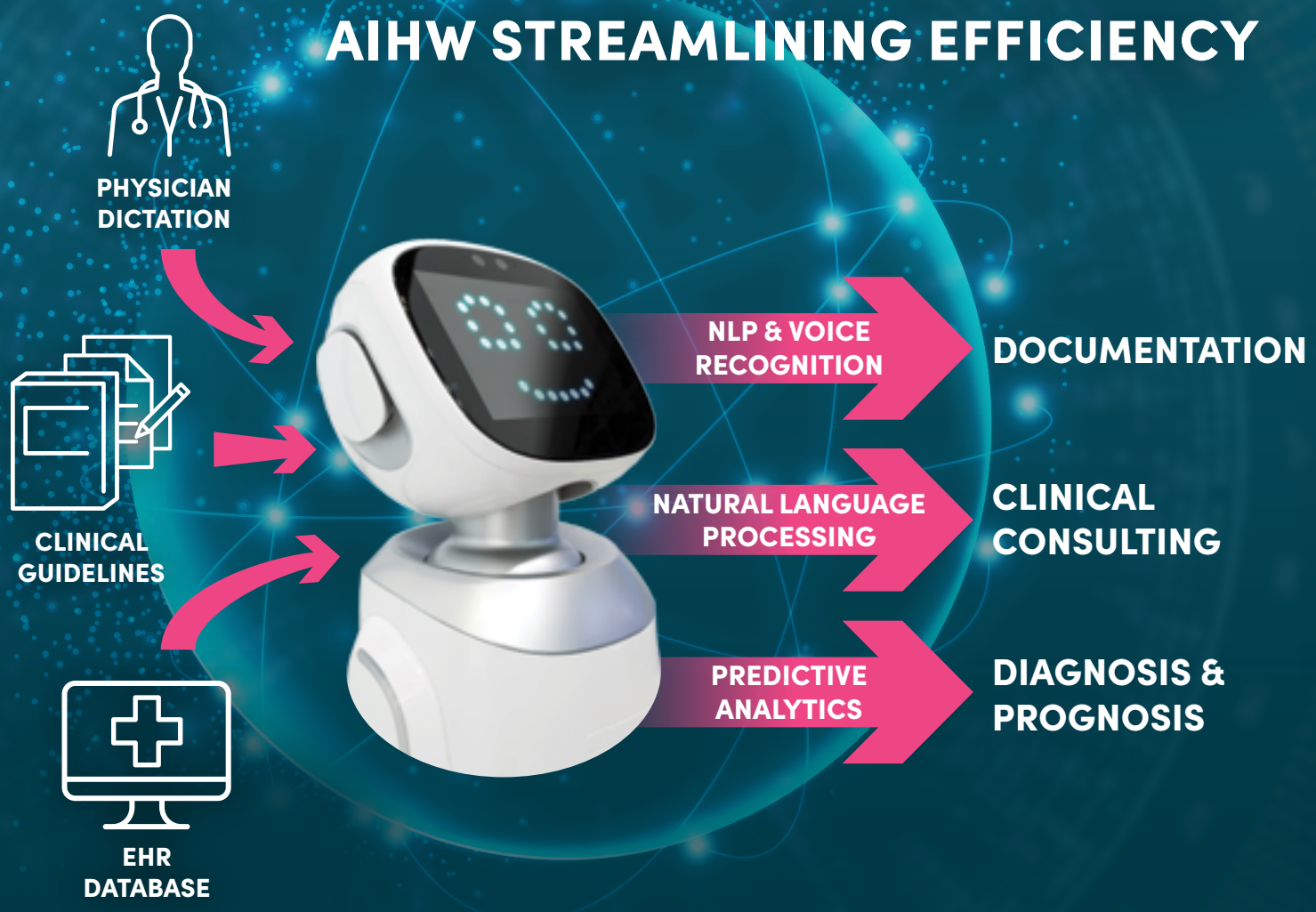
The most advanced data technologies combine predictive analytics with other AI subfields of data analytics such as natural language processing, speech detection and text mining. Oklahoma State University's Institute for Predictive Medicine (IPM) is actively tackling the physician shortage by leveraging AI and data analytics to develop innovative solutions. IPM executes this effort by working toward a multi-solution instrument known as an AI healthcare worker

(AIHW). The AIHW is a data-powered robotic assistant that streamlines physicians' roles with diagnostic, prescription, administrative and documentation duties.

The envisioned AIHW will consist of three modules for diagnosis, consulting and documentation, which all correspond to the three main verticals of activities of doctors, as illustrated in the figure below. The Diagnosis and Prognosis Module incorporates automatic machine learning algorithms to clean, analyze and model EHR data (including structured charts and unstructured data like images and EKGs) to generate and interpret accurate diagnosis/prognosis models for all possible conditions. In conjunction with sensors, cameras, EHR access and other data collection techniques, the models will allow the module to conduct independent, automatic examinations and diagnostics for patients.

Additionally, the Consulting Module incorporates natural language processing and text mining algorithms to automatically review medical literature and extract clinical guidelines and insights, which will be subsequently compiled into a repository of the module that provides proper medical suggestions or even prescriptions for the condition diagnosed.

Lastly, the Documentation Module incorporates voice recognition software for converting doctors' dictation into notes and natural language processing

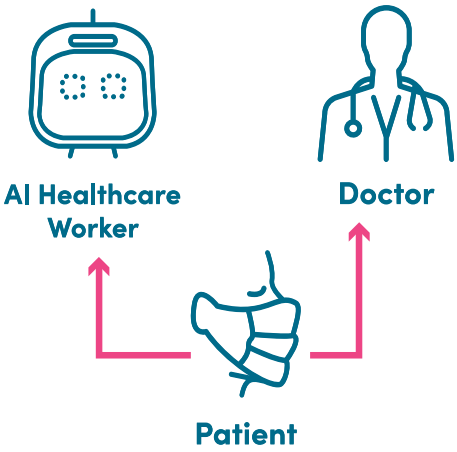


algorithms for extracting key clinical elements from the free-text notes. Natural language processing will convert dictated medical notes into structured EHRs and identify medical claims that need to be forwarded to insurance and billing partners — one of the major purposes of paperwork in medical practice. With this technique, doctors will be significantly freed up from their existing paperwork burden.

The AIHW will support doctors in the future healthcare practice with two care delivery models:

OPTIMAL CARE

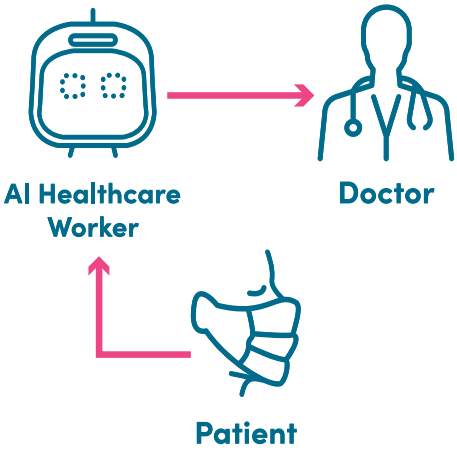
Examined by both AIHW and Doctor



In the first scenario, the doctor and AIHW are both available, as they would be in highly resourced clinical setting. The doctor and AIHW generate parallel, independent diagnoses and treatment options that allow the physician to double-check their diagnosis and treatment plan. The AIHW can scan millions of patient records and clinical guideline databases to generate a more precise diagnosis and treatment plan within seconds. This double-check system will help physicians catch clinical heuristic errors and deliver better care to patients more quickly. Ultimately, the AIHW will take over the majority of non-essential workload (e.g., data entry, paperwork and billing) from doctors and other healthcare practitioners, freeing up highly-trained healthcare personnel from administrative duties and allowing them to devote more time to patient care.

TIMELY CARE

Examined by AIHW and reviewed Doctor



In the scenario where a physician is not immediately available (such as in rural communities where the physician shortage is most pronounced), the AIHW can be deployed to provide preliminary diagnoses and treatment suggestions. The physician can supervise the AIHW through its audio, video and sensory telehealth capabilities and synchronously evaluate the AIHW's proposed diagnoses and treatment plan. The corrected and approved care will then be delivered promptly to save medically underserved patients precious time and travel costs.

IPM has been granted the use of Cerner Health Facts® — one of the largest EHR databases in the U.S. — to create the AIHW. Cerner Health Facts includes time-stamped admission, diagnosis, laboratory, vital sign, surgical and pharmacy data of over 487 million hospital visits. The database represents more than 68 million unique patients collected over the last 20 years from 880 U.S. hospitals running a Cerner EHR system.

The Cerner Health Facts dataset was used to create the diabetic retinopathy and readmission risk predictive models mentioned previously. By leveraging this massive health dataset, the IPM has created numerous AI models that can predict patient readmission risks, patient prognoses and optimal treatment plans.

The number of AI models produced from the Cerner Health Facts dataset proves that health data aggregation can catalyze the health data industry. Although Cerner Health Facts is one of the largest health datasets in the world, it can still expand and improve through data curation, representation and bias evaluation studies and collaboration with healthcare systems across the state. Through expansion, curation and improved representation, OSU's IPM health dataset will soon produce thousands of highly accurate AI models that will streamline clinical and administrative tasks to improve healthcare delivery and physician satisfaction.

CONCLUSION

Simply stated, the physician shortage currently exists across many states, and it is expected to worsen over the next few decades. This imbalance in supply is due to the country's rapidly growing elderly population, healthcare workflow inefficiencies and poor physician retention rates due to high levels of burnout. As a result, the shortage will affect the delivery of timely and adequate medical care, which will result in poor patient outcomes. This shortage will particularly impact patients with time-sensitive pathologies such as cardiac disease, stroke and cancer.

Steps have been taken to address this shortage, such as increasing the number of federally allotted Graduate Medical Education spots, also known as residency positions. Still, healthcare systems must expedite the development and adoption of health data technologies such as AI and ML tools to mitigate the effects of the shortage. Adopting AI tools will improve physician efficiency, satisfaction and retention to dampen the impact of the physician shortage and clinical care overload.

The U.S. healthcare system must become more efficient in using skilled medical talent to resolve supply and demand discrepancies. To combat the effects of the physician shortage, clinicians must operate at the top of their skill set to offer timely and high-quality care. Unfortunately, on average, U.S. physicians spend 44–50% of their time performing clerical tasks, and

this percentage is even higher in low-procedure specialties such as internal medicine and psychiatry[4]. To address the healthcare professional shortage, healthcare systems must consider AI tools that can lighten the burden of clerical tasks to allow doctors to provide timely and adequate medical care.

There are three major barriers to adopting AI solutions in medicine: the lack of representative structured datasets, skepticism toward adopting data solutions and a lack of agreement around how best to mitigate risk and demonstrate ROI for these tools. Improving interoperability is essential to compiling representative and unbiased datasets. Furthermore, healthcare stakeholders such as payors, providers, AI companies and data ethicists will need to work together to achieve consensus on governing, regulating and labeling health data to ensure patient protection, data privacy and excellent patient outcomes.

Centralization and curation of patient health data are necessary to expedite the development and adoption of health data tools. Additionally, centralized data systems need government, legislative, academic, ethics and advanced data industry support to preserve patient privacy, protection, diversity, representation and efficient usability. Healthcare is primed for the health data technology revolution. Today, a myriad of technological solutions and partners exist to make data exchange safe, ethical, and accessible. It is no longer a question of how but a question of when, where, and who will lead the health data industry into a period of exponential growth.

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ACKNOWLEDGMENTS

TIL and OSU's CHSI would like to thank the following field experts for contributing the time and knowledge that made this report possible.

Aaron Bean
Managing Partner,
Asemio

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