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The Future of Artificial Intelligence in the Healthcare Industry

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By

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Table of Contents

Chapter One:

Introduction to Research

Overview

Historians of technological advancement have struggled for decades with accurately relaying events of the past in a manner that is free from personal bias. In fact, their work repeatedly aims to "capture the spirit of the people and of the institutions they portray, and they have an eye for the telling anecdote. But their immediacy comes at the price of perspective." According to Michael Mahoney in "The History of Computing in the History of Technology," that perspective is negatively influenced by time in the sense that they are "guided by the current state of knowledge and bound by the professional culture. That is, its authors take as givens (often technical givens) what a more critical, outside viewer might see as choices. Reading their accounts makes it difficult to see the alternatives, as the authors themselves lose touch with a time when they did not know what they now know."[1] Consequently, articles on the fascination and excitement surrounding technological advancements may not always showcase reality in its

[1] Mahoney, Michael S. "The History of Computing in the History of Technology." *Princeton University*, The Trustees of Princeton University, www.princeton.edu/~hos/Mahoney/articles/hcht/hchtfr.html.

entirety; advancements and their beneficial contributions to society are routinely framed as inevitable or, as put by Mahoney, the "given." In turn, writers can subconsciously restructure the history of technology in a more positive light. By overshadowing any contempt, disagreement, or public disinterest at the time of a technology's development, they fail to piece the whole story together; they adhere to the "technical givens" and deprive outside viewers of understanding the other choices in that moment which, if selected, could have reoriented history's course.

As historians, archivists, and journalists continue to document the rapid pace of innovation, the line differentiating our choices in the face of new technologies is simultaneously diminishing. In essence, such rapid innovation has become the norm. It is difficult to accept any alternative when the ongoing race to bring the next greatest technology to market is a drive embedded into the culture of modern societies. Nevertheless, analyzing history and identifying trends through a more holistic lens is crucial in preparing for the future of technology ahead. With digital tools amassing unprecedented power, some innovations may risk transforming "the spirit of the people" and the "institutions they portray" in ways that do not align with a culture's values. This signifies the importance of taking precautions and considering a spectrum of choices before confirming the assumption that new technology is the solution in all facets of daily life. We must consider whether some innovations might actually hurt society and distinguish those facets in which technology is not the answer. Learning from history and detecting patterns throughout multiple technological eras offers valuable insights for doing so. Thus, the need is dramatically growing for authors to consider the times "when they did not know what they now know" within their work. Maintaining a holistic approach and accounting for what outside viewers may later see as choices can be accomplished through inquiries like, "How has the relationship between science and technology changed and developed over time and place? How do new technologies establish themselves in society, and how does society adapt to them? What role do governments play in fostering and directing technological innovation and development?"[2] This method assists in differentiating technological eras and distinguishing the events that have brought meaningful change.

Though we are currently living in the digital era, using these guiding questions to evaluate the descent of past ages - such as the industrialization period - indicates how that era could soon be coming to its end. Looking back to the 1830s amid the rise of Industrial America, "Michael Faraday invented the electric dynamo and motor. Still, it wasn't until 50 years later that Edison opened his first power plant, and then 40 years after that, during the 1920s, electricity began to have a measurable impact on productivity."[3] This manifests a pattern in which technological discovery leads to improved engineering followed by a transformation. Tracking that pattern from the beginning of the digital era up to modern day reveals how the "transformation" component to the digital revolution could be closing. The majority of digital tools introduced within the past five years have added more convenience to the market than innovation. Recent models of cell phones and laptops, for instance, are virtually no different than their last several predecessors – opening opportunities for new development to ignite another technological era. Of course, the most prominent question with an end to the digital era would be, "What is next?" Artificial intelligence appears to be answering that very question. Its potential to build upon every technological era of the past could culminate in a new phase of discovery, and perhaps no industry stands to benefit more so than the healthcare sector.

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[2] Michael, Mahoney S. "The History of Computing in the History of Technology." *Princeton University*, The Trustees of Princeton University, www.princeton.edu/~hos/Mahoney/articles/hcht/hchtfr.html.
[3] Satell, Greg. "The Industrial Era Ended, and So Will the Digital Era." *Harvard Business Review*, 13 July 2018, hbr.org/2018/07/the-industrial-era-ended-and-so-will-the-digital-era.

In anticipation of a new phase of discovery typified by artificial intelligence, access to large sets of data are becoming increasingly available to academic researchers, private sector leaders, and government officials. While the private sector has played an integral role in generating AI innovation focused on healthcare services, the need for government agencies and corresponding partners to improve their data sharing contributions is preventing additional progress. Still, researchers across numerous disciplines are capitalizing on the increased attention that healthcare AI is currently receiving, especially as it pertains to how AI can be implemented to improve both individual and public health. Accounting for the holistic structure of properly analyzing the history of technology, members of the AI community are reviewing how technologies related to or developed prior to artificial intelligence have led to today's status and circumstances within the medical setting. To consider the ways in which AI might establish itself in society, subsequently bringing the "discoveries" necessary to ignite another technological era, venture capitalist and author Kai-Fu Lee named four separate AI waves. As conceptualized in Figure 1.1, Lee suggests that "the first wave of AI applications uses data generated on the Internet to better understand the habits, interests, and desires of an individual or population. The second wave uses algorithms to inform and improve decision making. The third wave relates to the proliferation of sensors and devices that collect data about the physical world. The fourth wave integrates all previous waves and gives machines the ability to make decisions without human intervention."[4] These differentiations unveil how nations actually rank against competitors in terms of technological innovation - shedding light on what has been accomplished in healthcare AI development versus what needs to be done in order to meet societies' preconceived notions.

[4] "Sharing and Utilizing Health Data for AI Applications." *Home - Center for Open Data Enterprise*, Center for Open Data Enterprise, 16 Apr. 2019, www.opendataenterprise.org/publications.

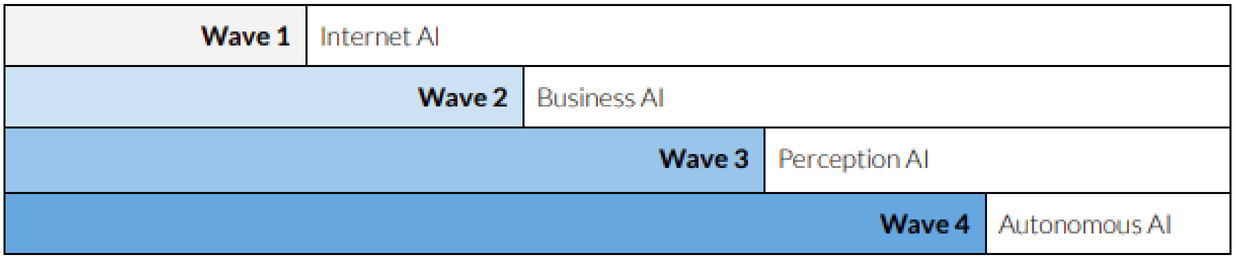

Figure 1. "The Four Waves of AI"
Adapted from Kai-Fu Lee (2018)

Figure 1.1: The Four Waves of AI
Source: Center for Open Data Enterprise

Upon closer observation of the technological tools used in healthcare services, it becomes apparent that Lee's waves have only been accomplished in practice to a certain degree. For instance, Wave 2 has enabled clinical researchers to create treatment plans for their patients guided by algorithms that "digest enormous quantities of data on patient diagnoses, genomic profiles, resultant therapies, and subsequent health outcomes."[5] Furthermore, Wave 3, labeled as perception AI, is representative of smart watches and virtual assistants - which have essentially enabled on-the-go health resources. Though these implementations have proven useful for multiple purposes within the medical field and beyond, leaders from academia, the private sector, and government are still grappling with possible implications of Wave 4: autonomous AI. MYCIN, a famous medical system from the 1970s based on rules taken from healthcare professionals, was one of the first complex systems provoking hesitation about technology's extent in health services. With approximately 600 rules, MYCIN's objective was to identify specific infections and then recommend proper antibiotics to patients. Despite the fact that it outperformed human doctors in trials at Stanford Medical School, MYCIN was never actually

[5] "Sharing and Utilizing Health Data for AI Applications." *Home - Center for Open Data Enterprise*, Center for Open Data Enterprise, 16 Apr. 2019, www.opendataenterprise.org/publications.

put into practice - due in part to “observers [raising] ethical and legal issues related to the use of computers in medicine. However, the greatest problem, and the reason that MYCIN was not used in routine practice, was the state of technologies for system integration, especially at the time it was developed. MYCIN was a stand-alone system that required a user to enter all relevant information about a patient by typing in responses to questions MYCIN posed. The program ran on a large time-shared system before personal computers were developed.”[6] Evidently, MYCIN was ahead of its time and could not yet benefit healthcare systems given the outdated backbone of the industry. However, even with personal computers and efficient computing programs as the norm in modern society, the same concerns at the time of MYCIN’s introduction remain significant today. In the face of autonomous AI and its potential to replace traditionally human-driven tasks, it is worth questioning - as the history of technology tells us to - how AI would establish itself in the medical field (assuming the healthcare industry could adapt its practices effectively) and whether AI technologies might even induce more harm than good in this specific facet.

Utilizing machine intelligence as opposed to human intelligence for the purposes of planning, offering solutions, and providing insights, artificial intelligence and its medical promise is dominating the narrative - despite uncertainty regarding its capacity in current systems. What *is* certain is that AI has the ability to alter traditional dynamics between doctors, patients, administrators, and other relevant parties in the healthcare industry; whether AI will bolster or hurt these dynamics is up for interpretation. Nevertheless, eagerness to deploy healthcare AI predominantly stems from its potential in clinical operations. In this setting, artificial intelligence can help to “effectively streamline diagnostic and treatment processes by

[6] “Mycin.” *Wikipedia*, Wikimedia Foundation, 17 Dec. 2020, en.wikipedia.org/wiki/Mycin.

using large amounts of structured and unstructured medical data across institutions."[7] Radiology and pathology are particularly expected to benefit from AI tools established for this purpose. The 2018 World Medical Innovation Forum on artificial intelligence even placed the pair among the "Disruptive Dozen," composed of the top 12 areas for which AI technologies are believed to have the greatest potential for impacting healthcare in the next decade. Primarily, approaching radiology with AI could enable "computers to scrutinize images for subtle variations and textures that human eyes cannot discern. That means automated methods for reading and interpreting CT scans, MRIs, and X-rays are within reach, giving radiologists new tools to systematically quantify image features and use them to help understand disease biology and predict outcomes."[8] These abilities offer tremendous hope for accurately diagnosing diseases such as prostate cancer, ranking among the leading cancers for men in the United States, by detecting malignant versus benign tumors in MRIs as well as pinpointing the most invasive subtypes. In the realm of pathology, developers are also seeking ways to improve the accuracy of disease prognosis. One research team in California, for example, has designed "an automated method that detects nearly 10,000 different features within whole-slide pathology images to distinguish different lung cancer subtypes and predict patient survival."[9] That feature would empower patients with adequate information to select the appropriate treatment plan for their unique life circumstances and specific health goals.

Of course, these possibilities for ameliorating radiology and pathology practices, alone, validate the elation at AI's future in clinical medicine, but with a new phase of discovery comes

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[7] Chebrolu, Kumar, et al. "Smart Use of Artificial Intelligence in Health Care." *Deloitte Insights*, www2.deloitte.com/us/en/insights/industry/health-care/artificial-intelligence-in-health-care.html/.

[8] *2018 Recap - World Medical Innovation Forum*. Partners Healthcare, worldmedicalinnovation.org/wp-content/uploads/2018/09/Partners-ZMAG-Forum-2018-Recap-180503_1202-ZMAG.pdf.

[9] *2018 Recap - World Medical Innovation Forum*. Partners Healthcare, worldmedicalinnovation.org/wp-content/uploads/2018/09/Partners-ZMAG-Forum-2018-Recap-180503_1202-ZMAG.pdf.

the fascination and excitement from ordinary citizens that historians of technological advancement and other journalists can consciously or subconsciously exploit. Although many of their publications do intend to merely capture the "spirit of the people" in response to the prospect of AI, the discussion has evolved in a way that falsely depicts the extent of artificial intelligence in the United States and beyond - proving the validity of Mahoney's argument. In actuality, how we define AI remains unclear on an international scale. The race to establish AI thereby cannot have a true finish line until its meaning is more transparent and consistent across literature with classifications that are widely agreed upon.

Discrepancies in AI Literature

Presently, one of the most common issues in AI literature is that machine learning is used interchangeably with artificial intelligence, despite the fact that it has been in practice for decades and AI has not. Classifying machine learning as artificial intelligence is not entirely inaccurate, albeit misleading. A tool focused "on building applications that learn from data and improve their accuracy over time without being programmed to do so,"[10] machine learning is a subfield of AI, yet not all AI is machine learning. This gray area has resulted in discrepancies across AI literature and is why a firm consensus on what constitutes artificial intelligence is so difficult to attain. Essentially, machine learning differs from AI in the sense that its "systems are focused on specific processes from which they are unable to deviate." Artificial intelligence, on the other hand, "can actually [begin] to make decisions for itself."[11] The machine would be capable of learning lessons in a specified area and applying that knowledge to a variety of other

[10] IBM Cloud Education. "What Is Machine Learning?" *IBM*, 15 July 2020, www.ibm.com/cloud/learn/machine-learning.
[11] Stephens, Gareth. "AI Isn't Taking over the World – It Doesn't Exist Yet." *GBG Global* , www.gbgplc.com/inside/ai/.

contexts. Hence, the distinction between true AI and what is falsely labeled as AI depends on where, how, and to what extent learning takes place. The scarcity of public education or simplified literature on this distinction has now led many people to believe that AI is fully "part of our daily lives, from greeting us in the morning through smart home devices, creating shopping lists, playing music, setting timers, and alerting us of a traffic jam on our expected route home,"[12] when true AI is arguably at just the cusp of its existence.

Without a national or international consensus on what constitutes true AI, additional assertions that the United States is among AI leaders is somewhat inaccurate and even dangerous to assume in the healthcare setting. It is, indeed, valid to affirm that multiple countries, including the U.S., are contributing to healthcare AI innovation everyday. Asia exhibits the quickest rate of growth - particularly in China. Europe boasts "vast troves of health data collected in national health systems and has an emerging strategy on how to ensure the 'EU way' for AI helps deliver the advantages for AI to its population." Though the United States "still dominates the list of firms with highest VC funding in healthcare AI to date, and has the most completed AI-related healthcare research studies and trials,"[13] it does not compensate for the insufficient data sharing capacity of the American healthcare system. Even with Europe's nationalized health system and guidance on how to exchange electronic health record information, McKinsey notes that "valuable data sets are not linked, with critical data-governance, access, and security issues still needing to be clarified"[14] before AI adoption. By this logic, if the European healthcare system is

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[12] Greene, Adam H. "More Data Please! The Challenges of Applying Health Information Privacy Laws to the Development of Artificial Intelligence: Davis Wright Tremaine." *Artificial Intelligence Law Advisor | Davis Wright Tremaine*, 26 Feb. 2020, www.dwt.com/blogs/artificial-intelligence-law-advisor/2020/02/ai-healthcare-privacy-laws.
[13] Spatharou, Angela, et al. "Transforming Healthcare with AI: The Impact on the Workforce and Organizations." *McKinsey & Company*, 13 Mar. 2020, www.mckinsey.com/industries/healthcare-systems-and-services/our-insights/transforming-healthcare-with-ai.
[14] Spatharou, Angela, et al. "Transforming Healthcare with AI: The Impact on the Workforce and Organizations." *McKinsey & Company*, 13 Mar. 2020, www.mckinsey.com/industries/healthcare-systems-and-services/our-insights/transforming-healthcare-with-ai.

unprepared for the integration of AI, the U.S. is undoubtedly further away from reaching the "finish line." Therefore, it would be premature to affirm that technological advancement in the form of artificial intelligence is the clear means to enhancing healthcare operations for the United States.

Methods and Data

This research ultimately finds that the U.S. cannot certify artificial intelligence as its definitive future for healthcare, nor should it overlook other viable options to better health services, so long as a firm definition is not clarified and the understructure of the American healthcare system lingers behind those achieved in Europe and Asia. Nonetheless, the paper aims to assess the healthcare changes proposed by AI and how they might impact relations among stakeholders if these underlying components are addressed. The research will first define AI in Chapter Two and discuss in detail the misconceptions surrounding what it is and what it is not. Differentiating the pair discloses where the United States actually stands in terms of AI development. Given that distinction, Chapter Three then analyzes the potential for artificial intelligence to benefit the healthcare industry versus the difficulties of putting it into practice. Doing this necessitates weighing the opportunities for systematic improvements - mainly as they relate to assisting clinician care teams - against the real-life experiences of providers experimenting with AI in their daily practices. As a result, the barriers to implementing healthcare AI are identified in Chapter Four, with substantial attention paid to electronic health record deficiencies delaying artificial intelligence even further. This is done through an empirical examination of EHRs by U.S. region and the extent to which varying systems can find, send, receive, and integrate clinical information. Data for this section is extracted from the American

Hospital Association Annual Survey, which publicizes information regarding health technology trends each year. The findings culminate in Chapter Five's recommendations for addressing barriers so that, if AI *can* one day integrate into medical practices, an optimal relationship may flourish between technology and healthcare.

Chapter Two:

Defining Artificial Intelligence

Overview

Differentiating what constitutes artificial intelligence versus machine learning, knowledge, or other tools is vital when it comes to the healthcare industry. With legal and ethical consequences always at stake, transparent distinctions can avert liability concerns and financial destruction - especially as they relate to privacy laws or access granted to protected health information. Thus, it is in the interest of all parties, including healthcare facilities, hospital systems at large, providers, and companies developing AI technologies, to understand what is and what is not artificial intelligence. Complicating matters is the reality that AI has become an umbrella term for numerous technological capabilities, rather than a specific type of machine demonstration, throughout various forms of literature. This has given marketers leverage to promote companies falsely claiming to use AI which, in turn, blurs public perception of artificial intelligence even more so. On those grounds, a stunning report from a London-based venture capital firm, MMC, found that "out of 2,830 startups in Europe that were classified as being AI companies, only 1,580 accurately fit that description." The numbers equated to a shocking 40% of European firms identified as AI startups failing to even "exploit the field of study in any material way for their business."[15] While this discrepancy can frequently be attributed to misconceptions of what should be labeled as AI, companies' claims to be using cutting-edge, breakthrough AI technologies is all too often another marketing tactic - for AI-related startups attract 15-50% more funding than regular tech firms.[16] Harvard Medical School professor and Cyft CEO Leonard D'Avolio confirms, "If I describe what I do as cognitive computing, but a competitor describes what they do as AI or machine learning or data mining, it's hard to even understand what problems we are trying to solve."[17] Unfortunately, healthcare has become a business, and making a profit requires mass marketing. D'Avolio's comments imply that problems arise on an industry level when it is unclear if health professionals are using legitimate technological terminology for given scenarios or if they are using the sophisticated language solely to advertise their practice. These professionals are also forced to wonder how other facilities are using technological dialogue, as their projected associations between technology and solving problems may clarify competitors versus complimenters. For this reason, misclassifications of AI must be corrected to ensure that health services are not compromised for business ventures and that the industry upholds a consistent vision for AI applications moving

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[15] Olson, Parmy. "Nearly Half Of All 'AI Startups' Are Cashing In On Hype." *Forbes*, Forbes Magazine, 5 Mar. 2019, www.forbes.com/sites/parmyolson/2019/03/04/nearly-half-of-all-ai-startups-are-cashing-in-on-hype/?sh=309e8183d022.

[16] Olson, Parmy. "Nearly Half Of All 'AI Startups' Are Cashing In On Hype." *Forbes*, Forbes Magazine, 5 Mar. 2019, www.forbes.com/sites/parmyolson/2019/03/04/nearly-half-of-all-ai-startups-are-cashing-in-on-hype/?sh=309e8183d022.

[17] Miliard, Mike. "Use Your Words! Sorting through the Confusing Terminology of Artificial Intelligence." *Healthcare IT News*, 6 Nov. 2018, www.healthcareitnews.com/news/use-your-words-sorting-through-confusing-terminology-artificial-intelligence#:~:text

forward. Outlining the unique qualities of knowledge, machine learning, deep learning, and artificial general intelligence in the following section aids in correcting those misclassifications.

A Timeline of Artificial Intelligence

The actual term, “artificial intelligence,” was first introduced by John McCarthy in 1956. During that decade, development of the perceptron, explained as “the first machine capable of having an original idea” and inspired by “stories about the creation of machines having human qualities,”[18] notably contributed to this new concept. Created by Frank Rosenblatt with an initial goal of designing an image recognition tool for the U.S. Navy, “the idea behind perceptrons (the predecessors to artificial neurons) is that it is possible to mimic certain parts of [human] neurons, such as dendrites, cell bodies and axons using simplified mathematical models of what limited knowledge we have on their inner workings: signals can be received from dendrites, and sent down the axon once enough signals [are] received. This outgoing signal can then be used as another input for other neurons, repeating the process.”[19] With the newfound potential for machines to learn like a human brain, rather than to constantly be trained by human instruction, media outlets began painting an unrealistic picture and inciting a new vision for the future of technology. One New York Times report in 1958 wrote, “The Navy [has] revealed the embryo of an electronic computer today that it expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence.”[20] This projection proved far too futuristic at the time, as the

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[18] Nagyfi, Richard. *The Differences between Artificial and Biological Neural Networks*. Towards Data Science, 4 Sept. 2018, towardsdatascience.com/the-differences-between-artificial-and-biological-neural-networks-a8b46db828b7.

[19] Nagyfi, Richard. *The Differences between Artificial and Biological Neural Networks*. Towards Data Science, 4 Sept. 2018, towardsdatascience.com/the-differences-between-artificial-and-biological-neural-networks-a8b46db828b7.

[20] Nagyfi, Richard. *The Differences between Artificial and Biological Neural Networks*. Towards Data Science, 4 Sept. 2018, towardsdatascience.com/the-differences-between-artificial-and-biological-neural-networks-a8b46db828b7.

shortcomings of perceptrons revealed that they were not artificial intelligence in their own regard. The perceptron could only place an input into one of two categories, and if it selected the wrong category, it corrected itself to prevent making the same error with other example data. It became clearer from these efforts that the machine could learn, but its applications to nonlinear relationships in data were restricted - meaning that perceptrons could only distinguish between two classes theoretically separable by a graphed line. Rosenblatt's mission to build "a machine capable of perceiving, recognizing and identifying its surroundings without any human training or control"[21] would therefore not be achieved for decades - when the use of multiple layers in perceptrons could challenge more complex data. Nevertheless, the impacts of promoting artificial intelligence too quickly in the 1950s produced an ongoing expectation for rapid innovation. Although acknowledgment of the perceptron's shortcomings led to the first "AI winter," characterized by decreased funding and support, society had already been given a wishful glimpse into "what could be" for the future of technology. In that sense, the race to bring the next best innovation to market never halted - nor did the people's anticipation for more. This same reality holds true today, especially when it comes to individuals' health.

Specific to the healthcare industry, reporting from popular media outlets now categorizes AI as "on a par with human experts when it comes to making medical diagnoses."[22] Other studies and literature predict AI-based systems will "bring specialist diagnostic expertise into primary care"[23] and now applaud the "use of artificial intelligence to speed up the diagnosis of

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[21] Nagyfi, Richard. *The Differences between Artificial and Biological Neural Networks*. Towards Data Science, 4 Sept. 2018, towardsdatascience.com/the-differences-between-artificial-and-biological-neural-networks-a8b46db828b7.

[22] Davis, Nicola. "AI Equal with Human Experts in Medical Diagnosis, Study Finds." The Guardian, Guardian News and Media, 24 Sept. 2019, www.theguardian.com/technology/2019/sep/24/ai-equal-with-human-experts-in-medical-diagnosis-study-finds.

[23] Buch, Varun H, et al. "Artificial Intelligence in Medicine: Current Trends and Future Possibilities." *The British Journal of General Practice : the Journal of the Royal College of General Practitioners*, Royal College of General Practitioners, Mar. 2018, www.ncbi.nlm.nih.gov/pmc/articles/PMC5819974/.

COVID-19 and improve the future treatment of patients."[24] It is worth noting that each of these referenced comments on AI's role in diagnosing come from European sources. During this research, there was oftentimes more detailed and reputable literature on healthcare AI coming from Europe than the United States. This is not to say that Europe has necessarily completed more research, studies, or trials than the U.S., but rather to acknowledge that European sources were most helpful in answering several research questions. Upon closer investigation and looking further into the range of sources covering what AI is and what its future in the healthcare industry might entail, it appears that Europe - and perhaps more specifically, the European Union - surpasses the United States on multiple accounts. According to a 2017 study conducted by the Center for Data Innovation, the EU had 43,064 AI researchers compared to the United States' 28,536 researchers. The EU also boasted 5,787 of the "Top AI Researchers (H-Index)," while the U.S. followed with 5,158. Most prominently, the EU published 14,776 AI papers in 2017, and the U.S. fell behind at 10,287.[25] Considering how that number of artificial intelligence papers encompasses all applications of AI - not solely that of the healthcare industry - it would be logical to assume that the lack of national consensus in the U.S. on what constitutes artificial intelligence for the medical field partially stems from insufficient published data on the matter; attention may be focusing too heavily on technical papers, when theoretical, definitional, and application-level research is still necessary. In light of this deficiency, the first step toward securing a better medical future is refraining from a rush to "capture the spirit of the people." Instead, attention must be diverted to clarifying a definition of AI and establishing *how* or conceivably *whether* the United States can safely and effectively apply it to such a critical

[24] "Using AI to Fast and Effectively Diagnose COVID-19 in Hospitals." Shaping Europe's Digital Future - European Commission, 29 Sept. 2020, ec.europa.eu/digital-single-market/en/news/using-ai-fast-and-effectively-diagnose-covid-19-hospitals.

[25] Castro, Daniel. "Who Is Winning the AI Race: China, the EU or the United States?" *Center for Data Innovation*, 30 Aug. 2019, datainnovation.org/2019/08/who-is-winning-the-ai-race-china-the-eu-or-the-united-states/.

industry. The subsequent chapters of this paper aim to contribute to that very conversation, with a focus in the next section on clarifying distinctions between knowledge, machine learning, deep learning, and artificial general intelligence.

Clarifying the Literature

Distinguishing artificial intelligence from other technological capabilities requires outlining the qualities of knowledge, machine learning, and AI that are different from one another - rendering each tool unique. The code developed in Image 2.1 - used for the purpose of infectious disease diagnosis - fundamentally exhibits why that distinction is central to this research. Nowadays, many technologies are written about as having used artificial intelligence, yet a myriad of those mechanics are actually accomplished through simple algorithms already in practice for decades. Incorporated into many of the algorithms is an "if, then statement," which simply tests for whether a condition is present in the given data. Since the inception of AI research, "if, then statements" have progressed to carry out convoluted tasks, yet even in rather straightforward series (such as that in Image 2.1), "if, then statements" can make up the core of seemingly advanced technologies. A renowned medical system highlighted by these characteristics is MYCIN, from which Rule 543 in Image 2.1 is derived. Constructed over roughly 6 years in the 1970s, MYCIN is now referred to by trusted sources - such as *Forbes* - as an "AI program designed to assist physicians by recommending treatments for certain infectious diseases."[26] Meanwhile, its Wikipedia page projects to millions of daily site visitors that the system "used artificial intelligence to identify bacteria causing severe infections, such as

[26] Press, Gil. "12 AI Milestones: 4. MYCIN, An Expert System For Infectious Disease Therapy." *Forbes*, Forbes Magazine, 27 Apr. 2020, www.forbes.com/sites/gilpress/2020/04/27/12-ai-milestones-4-mycin-an-expert-system-for-infectious-disease-therapy/?sh=1f5628de76e5.

bacteremia and meningitis, and to recommend antibiotics."[27] However, describing MYCIN as an application of AI would be invalid. The medical system, from which Rule 543 is derived, presents an alternative technological application: knowledge.

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RULE543
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  If:  1) The infection which requires therapy is meningitis,
       2) Only circumstantial evidence is available for this case,
       3) The type of the infection is bacterial,
       4) The patient is receiving corticosteroids,

  Then:  There is evidence that the organisms which might be
         causing the infection are e.coli (.4), klebsiella-pneumoniae (.2),
         or pseudomonas-aeruginosa (.1)
```

Image 2.1: Knowledge Demonstration in MYCIN's Rule 543
Source: Office of Naval Research

a. Knowledge

Rule 543 illustrates the technological application of "knowledge" as one of the 600 rules ingrained into MYCIN. To obtain these rules and integrate them into an algorithm, program designers consulted with medical doctors to determine probabilities for various diagnoses and how to advise the appropriate infectious disease therapy. Thus, no machine learning was required to get these rules; the computer did not have to learn any rules, itself, in order to produce results - nor did it need machine learning to acquire rules in the first place. Rather, a human coded each "if, then statement" based upon a provider's knowledge - giving the machine that knowledge in turn. Because the machine is limited to the knowledge it has been supplied with, MYCIN users cannot ask questions that the human designers have not programmed an answer for. All output from the model can be traced back by users to better understand how the computer reached an answer. In fact, "it can describe its reasoning steps: how a request for data is related to a goal,

[27] "Mycin." *Wikipedia*, Wikimedia Foundation, 17 Dec. 2020, en.wikipedia.org/wiki/Mycin.

how one goal leads to another, and how a goal is achieved."[28] Because of this, the primary benefit of computer "knowledge" for health applications is the explanation capability and autonomy for a user to inquire why or how a conclusion prevailed over others. The questioning session after a MYCIN consultation in Image 2.2 manifests that advantage. On the other hand, explanations would not necessarily be attainable in the case of machine learning or true artificial intelligence. With AI in particular, humans may never comprehend how a computer reaches an answer, as it learns a rule in one setting and then applies that new knowledge to another area in milliseconds. Exposing the machine to more data then allows it to continuously learn and adapt over time - all in ways that the human eye does not physically see. This encompasses the very reasons as to why AI is a debatable topic in healthcare, while "knowledge" incorporation has fewer risks.

***** DID YOU CONSIDER WHETHER THE PATIENT WAS RECEIVING STEROIDS?***

RULE543 could have used:
whether **J.Smith** has received corticosterotds.

Clause 4 of RULE543 {the patient has received corticosteroids) **was already** known to be false.

***** HOW DID YOU KNOW THAT THE PATIENT HAD NOT RECEIVED STEROIDS?***

RULE395 was used to conclude that J.Smith has **not received corticosteroids.** The last question asked before the conclusion was made **was 23.**

***** WHAT WAS QUESTION 23?***

Question 23 was asked in order to find out whether **J.Smithis a** compromised host in an effort to execute RULE343.

Figure 2, Excerpt from question/answer session
(User input appears in *BOLD ITALICS.)*

Image 2.2: Explanation Capability of MYCIN
Source: Office of Naval Research

[28] Clancey, William J. Office of Naval Research, 1981, *The Epistemology of A Rule-Based Expert System: A Framework for Explanation*, infolab.stanford.edu/pub/cstr/reports/cs/tr/81/896/CS-TR-81-896.pdf.

b. Machine Learning

In addition to qualities of "knowledge," discerning the traits of machine learning is paramount to subsequently define artificial intelligence. Whereas MYCIN "[involved] the explicit embedding of human knowledge and behavior rules into computer programs," machine learning takes a different approach "to teach the computer how to solve problems and gain insights from solving those problems. That's how the computer learns automatically, without human intervention or assistance: by observing and looking for patterns in data and using feedback loops to monitor and improve its predictions."[29] One successful application of machine learning within the healthcare industry has been predictive analytics. Its value mainly stems from the improvements made to operational management, personal medicine, and epidemiology. Regarding individual and population health, predictive analytics' insights allow providers to interpret previous trends in healthcare to then improve outcomes. Unlike in the example of "knowledge" for MYCIN's performance, predictive analytics does not require a hypothesis. By contrast, "the machine may not know what it's looking for but as it processes the data it starts to identify complex processes and patterns that a human may never have identified." Learning is thereby achieved when a machine "uses an algorithm to seek patterns and structure in data and cluster them into groups or insights."[30] This process is clarified in Figure 2.3, showing how a patient going to the hospital and whether they are readmitted or not readmitted sparks a machine learning outcome loop. According to the model, patient characteristic, intervention, and outcome information is added into a data science engine and becomes part of a dataset. Its features are used to create a predictive model, and the predictive model assigns probabilities. From there, the

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[29] Verani, Estelle. "Symbolic AI vs Machine Learning in NLP (Natural Language Processing)." *Inbenta*, 1 July 2020, www.inbenta.com/en/blog/symbolic-ai-vs-machine-learning/.
[30] Watson, Kylie. "Predictive Analytics in Health Care." *Deloitte Insights*, www2.deloitte.com/us/en/insights/topics/analytics/predictive-analytics-health-care-value-risks.html#endnote-sup-2.

patient's outcome is predicted - determining whether they are readmitted or not readmitted. That prediction becomes visible to the clinician, who can use it to intervene appropriately with new patients as the cycle continues. Figure 2.3 is followed by an example of rules learned by a machine from an inputted medical diagnosis dataset in Figure 2.4. The "if, then statements" outputted by Figure 2.4 may appear similar in form to the case of MYCIN, but the associations connecting the "if" to "then" were detected by the machine in this case - not human intervention or given knowledge. Consequently, machine learning and predictive analytics' benefit to healthcare applications "is that they are stated in terms of the input features, without relying on any latent variables or representations, and they use concise, logical rules to make interpretable predictions."[31] Still, the current crop of articles and excitement surrounding machine learning are not referencing these kinds of models; they are fantasizing about AI. This overlooks the interpretability and high explainability of many machine learning applications while centering the narrative on a more unexplainable technology, which societies cannot concisely define.

[31] Lakkaraju, Himabindu, et al. "Interpretable Decision Sets: A Joint Framework for Description and Prediction." *KDD : Proceedings. International Conference on Knowledge Discovery & Data Mining*, U.S. National Library of Medicine, Aug. 2016, www.ncbi.nlm.nih.gov/pmc/articles/PMC5108651/.

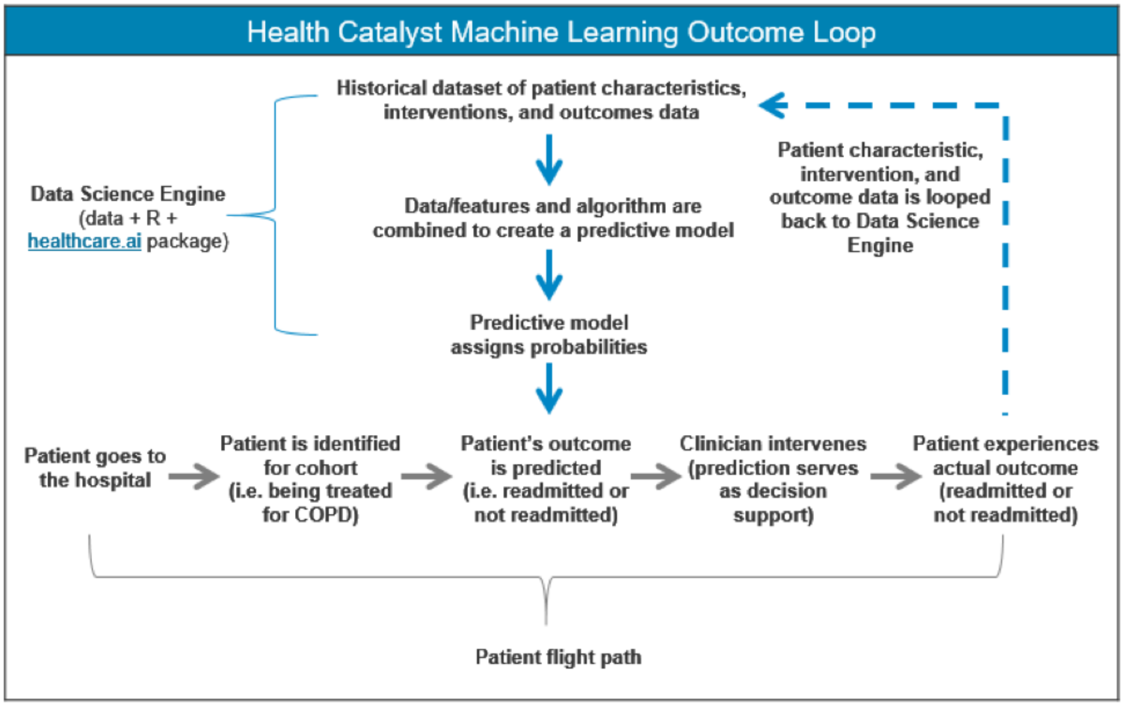

Figure 2.3: Machine Learning Diagram
Source: Health Catalyst

If Respiratory-Illness=Yes **and** Smoker=Yes **and** Age$\geq$ 50 **then** Lung Cancer

Else if Risk-Depression=Yes **then** Depression

Else if BMI $\geq$ 0.2 **and** Age$\geq$ 60 **then** Diabetes

Else if Headaches=Yes **and** Dizziness=Yes, **then** Depression

Else if Doctor-Visits$\geq$ 0.3 **then** Diabetes

Else if Disposition-Tiredness=Yes **then** Depression

Else Diabetes

Image 2.4: Results of Machine Learning
Source: U.S. National Library of Medicine

c. Deep Learning

The caliber of machine learning has undoubtedly been impressive and proven useful for our everyday lives - as evidenced through the medical implementation above. However, those with less technical backgrounds - and even those with some degree of technical experience - have been misled into trusting these applications to be artificial intelligence when, in actuality, deep learning remains the closest tool society has to true AI. Thus, to finish sorting through the multitude of distinctions in data science relevant to this research, it is necessary to distinguish between deep learning and artificial general intelligence: a term that is not nearly discussed as much as it should be in dialogues related to technology in healthcare.

Machine learning was previously discussed as a subfield of AI, but that subfield also has its own branches. Deep learning is one of those extensions, and it is arguably receiving the most attention in technological development at the moment. For the purposes of differentiating deep learning from true AI and ultimately securing a firm AI definition, it is useful to analyze the language incorporated into public statements by prominent members of the computer science community. Andrew Ng, a recognized supporter of deep learning, "has gone so far to suggest that 'If a typical person can do a mental task with less than one second of thought, we can probably automate it using AI either now or in the near future.'"[32] The New York Times Sunday Magazine added "that the technique is 'poised to reinvent computing itself.'"[33] From these two comments alone, it is crucial to note that automation does not equate to intelligence; this is what fundamentally separates machine learning and deep learning from artificial general intelligence. Deep learning is somewhat approaching the public's portrayal of AI in the sense that it depends

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[32] Ng, Andrew. "Andrew Ng: What AI Can and Can't Do." *Harvard Business Review*, 21 Sept. 2017, hbr.org/2016/11/what-artificial-intelligence-can-and-cant-do-right-now.
[33] Lewis-Kraus, Gideon. "The Great A.I. Awakening." *The New York Times*, The New York Times, 14 Dec. 2016, www.nytimes.com/2016/12/14/magazine/the-great-ai-awakening.html.

on hidden layers within a neural network, which are concealed from the human eye, in order to reach a result. In essence, "the mission of a typical network is to decide which of a set of categories (defined by the output units on the neural network) a given input belongs to." This process is demonstrated in Figure 2.5, whereby the network might be training "large sets of handwritten digits (these are the inputs, represented as images) and labels (these are the outputs) that identify the categories to which those inputs belong (this image is a 2, that one is a 3, and so forth)."[34] While a deep learning system's capacity to rapidly detect patterns is truly remarkable, that capacity is inherently limited considering deep learning lacks the tools to understand causation versus correlation. In the example of a neural network's image recognition training, the machine may learn that images of males are classified as a 1 and females are classified as a 2, but it cannot actually comprehend what gender is. On the contrary, it has solely identified characteristics from an image's pixels that, along with the pixels from other training data, match the criteria for a certain output. As a result, deep learning is more symbolic of intelligent automation than true AI, as the "word 'deep' in deep learning refers to a technical architectural property (the large number of hidden layers used in modern neural networks) rather than a conceptual one (the representations acquired by such networks don't, for example, naturally apply to abstract concepts like 'justice,' 'democracy' or 'meddling.'"[35] Due to these limitations, the press should not publicize deep learning as the successful solution to artificial intelligence, regardless of whether it is technically considered a subset of AI. The fact of the matter is, without any understanding of the real world, deep learning exhibits no palpable "intelligence."

[34] Dickson, Ben. "The Limits and Challenges of Deep Learning." *TechTalks*, 11 Aug. 2019, bdtechtalks.com/2018/02/27/limits-challenges-deep-learning-gary-marcus/.
[35] Brownlee, Jason. "What Is Deep Learning?" *Machine Learning Mastery*, 14 Aug. 2020, machinelearningmastery.com/what-is-deep-learning/.

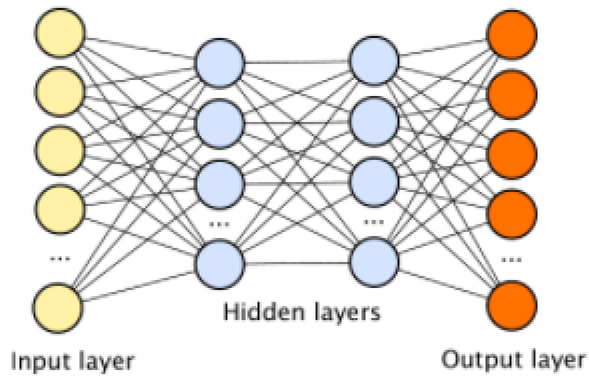

Figure 2.5: Deep Learning Hidden Layers
Source: TechTalks

d. Artificial General Intelligence → Artificial Intelligence

Given humans' inability to review the inner workings of hidden layers in neural networks and the absence of machine intellect, deep learning's proposed applications to healthcare services are already questionable - let alone the prospect of AI applications. As put by Gary Smith, author of *The AI Delusion* and Professor of Economics at Pomona College, "computers don't have any critical thinking skills. They have no common sense or wisdom. They don't understand the world in any real sense." Adopting such a mindset that computers have no authentic grasp on reality already makes the prior perspective of deep learning being "poised to reinvent computing itself" a difficult notion to lay hold of. The concept of then giving so much attention, trust, and funding to a machine presently deficient in critical thinking, common sense, and wisdom additionally makes reinvented computing through deep learning quite concerning. For those reasons, this paper ascertains that artificial intelligence must connote the hypothetical intelligence of a computer produced by the establishment of artificial general intelligence - recognized as the futuristic "intelligence of a computer program that has the capacity to understand or learn any intellectual task that a human being can."[36] Although experts differ in what they believe should be the criteria for "intelligence," it is generally agreed upon that artificial general intelligence should be able to "reason, use strategy, make judgements under uncertainty, represent knowledge (including commonsense knowledge), plan, learn, communicate in natural language, and integrate all these skills towards common goals."[37] How these characteristics will be achieved remains unclear, but its high standards to resemble human thinking show that we have a long way to go before they are possible.

The meaning behind "intelligence" further reveals how the popular press' references to artificial intelligence are primarily deep learning applications, with additional confusion added if referencing machine learning or computer knowledge techniques as AI. For these misinterpretations to be resolved, AI must represent the state at which a machine can finally prove its critical thinking skills, common sense, wisdom, or real understanding of the world - so as to avoid the other technological applications discussed in this paper being grouped into "artificial intelligence." Thus, AI would virtually adopt the definition of the less popular term - artificial general intelligence. Considering artificial general intelligence is known among researchers to be synonymous with full AI, strong AI, general intelligent action, and other terms largely unheard of by the greater public, consolidating the definition of artificial intelligence in this manner aims to diminish the false overlaps advertised by media outlets, marketers, and other tech companies. While former objectives for AI may have been more encompassing of applications like machine or deep learning through human designers, we can "no longer assume that the objective is fixed and known by the AI system; instead, the system may be uncertain

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[36] "Artificial General Intelligence." *Wikipedia*, Wikimedia Foundation, 27 Mar. 2021, en.wikipedia.org/wiki/Artificial_general_intelligence.
[37] "Artificial General Intelligence." *Wikipedia*, Wikimedia Foundation, 27 Mar. 2021, en.wikipedia.org/wiki/Artificial_general_intelligence.

about the true objectives of the humans on whose behalf it operates. It must learn what to maximize and must function appropriately even while uncertain about the objective."[38] Functioning in that manner requires a level of intelligence from machines that is currently nonexistent, even with deep learning. This reflects a greater trend in that, as the bar is set higher and higher for AI along with society's demands for what is wanted out of it, the definitions surrounding artificial intelligence are not keeping up. Consequently, much of the confusion surrounding what AI is and what it is not likely involves outdated terminology.

The notion of AI definitions failing to keep pace with rising standards is supported by the reality of researchers now referring to technologies not attempting to mimic the brain as "weak AI" in order to differentiate it from "strong AI." This definition is surely not reasonable; no marketing professional, tech company, or healthcare facility would want to advertise a tool using "weak AI." Herein lies the issue once again. To avoid these discrepancies, references to AI in the rest of the paper will signify the hypothetical, human-like intelligence of a machine illustrated through critical thinking, common sense, and wisdom. Having affirmed a definition of artificial intelligence for the purposes of this research, the following chapter explores the potential impacts for a machine's tangible sense of the real world versus its difficulties in practice within the healthcare setting.

[38] Russell, Stuart J., and Peter Norvig. *Artificial Intelligence: A Modern Approach*. 4th ed., Pearson, 2021.

Chapter Three:

Potential Benefits of Healthcare AI vs. Difficulties in Practice

Overview

In light of Chapter Two's discussion on the contradictory language surrounding artificial intelligence and its conclusion on a clearer AI definition for this research, Chapter Three reevaluates the benefits currently being proposed for healthcare AI. It is paramount to keep in mind that each of these proposed benefits are not guaranteed; artificial intelligence's applications to the healthcare industry and beyond must still be regarded as *potentials*, not *givens*, to prevent literature from further casting the "spirit of the people" in a manner that adds to false narratives on AI's presence. The National Academy of Medicine is thus cited in this section as one of the many sources to have acknowledged "gaps in evaluation of [AI] tools in peer-reviewed literature, [making] it difficult to assess their impact."[39] Nevertheless, it remains worthwhile to understand the promising aspects of AI in the medical field - as they demonstrate the scale of work that must be done if these solutions are to ever be achieved in the future.

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[39] "Artificial Intelligence Special Publication: The Hope, the Hype, the Promise, the Peril." *National Academy of Medicine*, 4 May 2020, nam.edu/artificial-intelligence-special-publication/.

Table 3.1 below offers a glimpse into this future in terms of how multiple stakeholder groups - including patients and families, clinician care teams, public health program managers, and business administrators - could advantage from AI in the medical field. While artificial intelligence could certainly play a large role in the futures of each of these stakeholder groups, the chapter will focus solely on “clinician care teams” from this table - with analyses chiefly related to the “early detection, prediction, and diagnostic tools,” “surgical procedures,” “precision medicine,” and “patient safety” categories under that case group. The logic behind selecting this category on its own is that provider performance impacts all other user groups from the table, especially patients and families. Perhaps the most important impact with the introduction of AI would be how the relationship between clinician care teams and patients is altered. Patients and their families depend on clinician care teams’ decision-making being in their best interest. Thus, their performance with new AI tools has high risk and high reward. If providers improve their daily practices by using AI tools, patients and families experience better outcomes; if providers worsen in their daily practices by using AI tools, patients and families experience negative outcomes. This could certainly feel like a daunting task for clinicians and their teams. To convey providers’ sentiments toward putting healthcare AI solutions into practice, the day-to-day optics with technology of Bellevue Hospital Attending Physician Danielle Ofri are drawn upon in the last section of this chapter to better weigh the potential benefits of AI against the potential consequences of AI in the healthcare industry. That perspective ultimately suggests that evaluating potential harms of healthcare AI is of equal, if not more, importance to evaluating potential benefits.

Use Case or User Group	Category	Examples of Applications	Technology
Patients and families	Health monitoring Benefit/risk assessment	• Devices and wearables • Smartphone and tablet apps, websites	Machine learning, natural language processing (NLP), speech recognition, chatbots
	Disease prevention and management	• Obesity reduction • Diabetes prevention and management • Emotional and mental health support	Conversational AI, NLP, speech recognition, chatbots
	Medication management	• Medication adherence	Robotic home telehealth
	Rehabilitation	• Stroke rehabilitation using apps and robots	Robotics
Clinician care teams	Early detection, prediction, and diagnostics tools	• Imaging for cardiac arrhythmia detection, retinopathy • Early cancer detection (e.g., melanoma)	Machine Learning
	Surgical proce-dures	• Remote-controlled robotic surgery • AI-supported surgical roadmaps	Robotics, machine learning
	Precision medicine	• Personalized chemotherapy treatment	Supervised machine learning, reinforcement learning
	Patient safety	• Early detection of sepsis	Machine learning
Public health program managers	Identification of individuals at risk	• Suicide risk identification using social media	Deep learning (convolutional and recurrent neural networks)
	Population health	• Eldercare monitoring	Ambient AI sensors
	Population health	• Air pollution epidemiology • Water microbe detection	Deep learning, geospatial pattern mining, machine learning
Business administrators	International Classification of Diseases, 10th Rev. (ICD-10) coding	• Automatic coding of medical records for reimbursement	Machine learning, NLP

Table 3.1: Potential for AI Applications by Stakeholder Group
Source: National Academy of Medicine

Proposed Benefits of AI for Clinician Care Teams

The proposed benefits of artificial intelligence for clinician care teams are placed into four categories - the first being early detection, prediction, and diagnostic tools, the second being surgical procedures, the third being precision medicine, and the fourth being patient safety. At present, medical errors are tainting the U.S. healthcare system and preventing additional success in these four categories, with "most patients experiencing at least one error in their lifetime"[40] It is extremely difficult in many cases to assert that a medical error was made, as evidenced by wide variations in data. However, there *is* wide agreement that the number of errors is too significant to ignore. This is not a new concept - from the "first Institute of Medicine report in 1999 that estimated 44,000 to 98,000 deaths per year from medical error to [a *British Medical Journal*] analysis suggesting upward of 250,000 deaths per year."[41] Given the continued frequency of such errors, there are evidently flaws in the healthcare system requiring immediate attention. These flaws largely emanate from a toxic medical culture in which doctors are expected to be all-knowing, resulting in their fears of asking for help or second opinions. But despite autonomy and self-sufficiency appearing admirable in certain cases, the complexity of modern medicine and our evolving knowledge on the human brain and body show that patient care cannot always be accomplished on one's own. Even the country's top surgeons, like Atul Gawande, are recognizing that group efforts are often necessary in order to benefit patients. He remarks, "We've now discovered 4,000 medical and surgical procedures. We've discovered 6,000 drugs that I'm now licensed to prescribe. And we've reached the point where we've realized, as

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[40] "Sharing and Utilizing Health Data for AI Applications." *Home - Center for Open Data Enterprise*, Center for Open Data Enterprise, 16 Apr. 2019, www.opendataenterprise.org/publications.
[41] Ofri, Danielle. *When We Do Harm: A Doctor Confronts Medical Error*. Beacon Press, 2020.

doctors, we can't know it all. We can't do it all by ourselves."[42] Without addressing this unsustainable culture in medicine, the detection and prediction methods contributing to medical errors will remain unchanged, fatal mistakes may continue during surgical procedures, patient safety could be jeopardized, and precision medicine will not be trusted. In essence, the field's inner toxicity would be unfixed at patients' expense, and the potential for AI applications to assist clinician care teams in their day-to-day responsibilities would never come to fruition. However, AI's potential to sort through hundreds of thousands of datasets, image pixels, or other records in milliseconds has been proposed as a solution to these dilemmas - paving way for minimized errors and maximized utility within the aforementioned categories for clinician care teams and, as a result, patients and their families.

a. Early Detection, Prediction, and Diagnostic Tools

The first category of potential AI benefits for clinician care teams is early detection, prediction, and diagnostic tools. As mentioned in Chapter One, pathology is a key realm in which developers are exploring AI's potential impact on this category - especially in terms of improving diagnosis. Considering that "seventy percent of all decisions in healthcare are based on a pathology result," empowering pathologists with effective AI tools could enhance diagnostic accuracy, reduce medical errors, and minimize preventable deaths in turn. Jeffrey Golden, MD, Chair of the Department of Pathology at Brigham and Women's Hospital and a professor of pathology at Harvard Medical School, comments that "somewhere between 70 and 75 percent of all the data in an [electronic health record] are from a pathology result. So the more accurate we get, and the sooner we get to the right diagnosis, the better we're going to be. That's

[42] Gawande, Atul. "How Do We Heal Medicine?" *TED*, www.ted.com/talks/atul_gawande_how_do_we_heal_medicine?language=en.

what digital pathology and AI has the opportunity to deliver."[43] The machine's ability to look closely into an image's pixels is a clear advantage over humans - for small nuances at the pixel level can easily go unnoticed by a pathologist. Not only that, but Golden indicates how AI tools could pinpoint specific areas of interest in a pathology slide for humans to then review, thereby addressing Gawande's comments that doctors cannot know or remember everything. He says, "AI can screen through slides and direct us to the right thing to look at so we can assess what's important and what's not. That increases the efficiency of the use of the pathologist and increases the value of the time they spend for each case."[44] The added efficiency could therefore equip pathologists to narrow the range of possibilities for a patient's ultimate diagnosis - diminishing the need to run through an ordinary, generalized symptom checklist and instead offering more opportunities for useful diagnostic support. In essence, implementation of such tools could not only benefit patients in their diagnosis, prognosis, and patient experience, but it could also transform the medical culture in which doctors refrain from asking for other practitioners' input.

b. Patient Safety and Surgical Procedures

In addition to early detection, prediction, and diagnostic tools, patient safety and surgical procedures are two proposed categories for AI's potential benefit. One of the ways in which patient safety may advance from artificial intelligence is through AI's possible role in the development of new therapeutics. As it currently stands, ensuring the efficacy and safety of new

[43] Bresnick, Jennifer. "Top 12 Ways Artificial Intelligence Will Impact Healthcare." *HealthITAnalytics*, HealthITAnalytics, 25 Aug. 2020, healthitanalytics.com/news/top-12-ways-artificial-intelligence-will-impact-healthcare.

[44] Bresnick, Jennifer. "Top 12 Ways Artificial Intelligence Will Impact Healthcare." *HealthITAnalytics*, HealthITAnalytics, 25 Aug. 2020, healthitanalytics.com/news/top-12-ways-artificial-intelligence-will-impact-healthcare.

drugs before entering the market is a timely process - with high expenses and inevitable setbacks during research trials also contributing to lengthy durations. Artificial intelligence is viewed as a mechanism to combat those delays and costs, specifically by identifying areas for improvement in pharmaceuticals and the shortcomings of today's therapeutics. Professionals are currently looking at the implications of using AI in this manner "to sort through huge numbers of research papers and patents, as well as comprehensive lists of chemical compounds and their properties, to suggest opportunities for drug development. By analyzing the growing databases of biomarker data, they can then work to target different treatments to different types of patients. And when drugs or other treatments reach the clinical trial stage, AI can help match ideal patients to the right trials."[45] The U.S. Department of Health and Human Services (in partnership with TrialX and Intel experts) is one group working toward greater clinical trial participation - using an AI application for matching individuals to relevant clinical trials suitable for their health circumstances. This is beneficial for all involved parties and their roles in ensuring patient safety. Researchers could be able to find appropriate candidates for their trials and providers could have other viable therapeutic options for those not responding well to traditional treatment plans - both parties with greater confidence that their actions will not induce harm on to the patient. A similar concept applies to surgical procedures and its potential for added patient safety measures. The hope behind AI in surgical settings is that it can reduce risk during surgery by providing more accurate roadmaps to success in the operating room. The roadmaps would "bear diverse sources of information, including patient risk factors, anatomic information, disease natural history, patient values and cost, to help physicians and patients make better predictions regarding the consequences of surgical decisions." Already, "a deep learning model [has been] used to predict

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[45] "Artificial Intelligence Special Publication: The Hope, the Hype, the Promise, the Peril." *National Academy of Medicine*, 4 May 2020, nam.edu/artificial-intelligence-special-publication/.

which individuals with treatment resistant mesial temporal lobe epilepsy would most likely benefit from surgery (Gelichgerrcht et al., 2018).”[46] AI could theoretically build upon this deep learning model for even more precise decision-making and suggested surgical techniques. This continues to address Gawande’s point that a singular surgeon or provider cannot remember all relevant medical information on their own, but the power of AI could theoretically aid these individuals and their teams - bolstering patient safety in turn.

c. Precision Medicine

The final category for which AI is proposed to benefit clinician care teams is precision medicine. Startups such as Lam Therapeutics and Lantern Pharma are exploring how AI applications might allow for precision medicine - defined by the National Institutes of Health as “an emerging approach for disease treatment and prevention that takes into account individual variability in genes, environment and lifestyle for each person.” Research is now focusing on supervised machine learning techniques “[generating] new correlations between genomic biomarkers and drug activity.”[47] This has the potential to bring individualized treatment plans to many more cancer patients. Until then, research pursuits will continue toward affirming the capacity of AI in new therapeutics. Nonetheless, achieving artificial intelligence in the healthcare industry could add individualized treatment plans beyond the realm of serious cancers; personalized interventions may also be possible for addressing more common health concerns before they develop into serious threats or crises. These interventions are known as “just-in-time adaptive interventions,” or JITAIs. They specialize in making “decisions about when and how to

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[46] “Artificial Intelligence Special Publication: The Hope, the Hype, the Promise, the Peril.” *National Academy of Medicine*, 4 May 2020, nam.edu/artificial-intelligence-special-publication/.
[47] “Sharing and Utilizing Health Data for AI Applications.” *Home - Center for Open Data Enterprise*, Center for Open Data Enterprise, 16 Apr. 2019, www.opendataenterprise.org/publications.

intervene based on response to prior intervention, as well as on awareness of current context, whether internal (mood, anxiety, blood pressure), or external (e.g., location, activity)."[48] Given the onset of these triggers, JITAIs are able to assist users at their greatest times of need. One possible application is sensing whether individuals treated for alcoholism are at risk of relapse in a particular environment. In that setting, the user would likely be receptive to assistance and the clinician team could be alerted of the potentially dangerous scenario - adding another source for timely intervention.

Difficulties in Practice: A Doctor's Perspective

Certainly, the prospect of artificial intelligence encaptured in the "spirit of the people" combined with the previously discussed, potential benefits of applying AI to healthcare services seems like a desirable tactic for improving the healthcare industry on the whole. However, taking into account the perspective of providers and clinician care teams, who would be most influenced by these changes, uncovers a conflicting message. The documented experiences of Dr. Danielle Ofri from Bellevue Hospital in New York perfectly depict the drawbacks of technology in health services - especially as those technologies advance even more so toward AI. To Ofri, accomplishing diagnostic support using AI would mean having "a system in which you could enter the patient's symptoms, and the program would create an accurate differential diagnosis. It would include all the rare diseases that fallible humans tend to forget but, of course, eliminate the ones that are too far out in left field. It would generate an intelligent road map for a thorough - but not reckless - workup. It would take into account cost efficiency and clinical

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[48] "Artificial Intelligence Special Publication: The Hope, the Hype, the Promise, the Peril." *National Academy of Medicine*, 4 May 2020, nam.edu/artificial-intelligence-special-publication/.

context and assiduously avoid both false-positive and false-negative errors."[49] While this type of system would be somewhat of a "holy grail" for many providers, Ofri's experiments with several diagnostic tools - namely ISABEL, VisualDx, and DXplain - manifest the major difficulties of putting AI technologies into practice.

To test out these diagnostic systems, Ofri and her team would enter symptoms for new cases into the machine and simultaneously determine how they would diagnose the patient without the technology. She then pressed "submit" in the system and compared her own differential diagnoses with those of the AI system. One case, in particular, producing contrasting diagnoses "involved a young, healthy woman in her early twenties who was experiencing episodes of rapid heart rate and shortness of breath. She'd previously played on sports teams but was now too fatigued to do so. Financial difficulties had recently forced her family to move into a cramped basement apartment. She disliked it intensely and felt very anxious whenever she was alone in the apartment."[50] In consideration of the non-medical factors impacting the patient's life, the cardiologist was confident that the rapid heart rate and shortness of breath were attributable to anxiety. However, the diagnostic system had entirely different explanations. Entering initial symptoms like tachycardia and dyspnea to account for the racing heart rate and shortness of breath "brought up a voluminous list of possible diagnoses. The system was casting a wide net so that it wouldn't miss anything, but humans wouldn't have wasted an iota of mental effort on a good chunk of their diagnoses. For example, the list was headed up by 'septic shock' - which of course can present with those symptoms. But when you are evaluating a healthy-appearing woman who is smiling and chatting amiably with you, septic shock would never enter your mind. Nor would massive hemorrhage or ruptured aortic aneurysm - two other diagnoses that

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[49] Ofri, Danielle. *When We Do Harm: A Doctor Confronts Medical Error*. Beacon Press, 2020.
[50] Ofri, Danielle. *When We Do Harm: A Doctor Confronts Medical Error*. Beacon Press, 2020.

appeared on the list."[51] This experience demonstrates one of the biggest drawbacks for AI in healthcare: machines struggle to capture the patient holistically and to contextualize.

In the case of this young woman, the systems did not offer a place for the provider to enter any potential psychosocial impacts on health - including the financial stress and feelings of claustrophobia in her new apartment. Ofri adds, "I don't fault the system for this, but these limitations highlight the breadth of the elements that enter into the diagnostic process."[52] Consequently, even if true AI were accomplished and diagnostic support systems exhibited the necessary critical thinking skills, common sense, wisdom, or understanding of the real world, they would likely still be unable to think about a patient's unique life circumstances and all the possible non-medical factors playing into a diagnosis in the same manner that human doctors would. Furthermore, it feels far-fetched that an AI diagnostic system could fully perceive the essence of what this patient was like as a person or contemplate the seemingly disconnected variables - like how a basement apartment's likelihood for mold could have a role in these health issues. Other pertinent questions for diagnosing that an algorithm might not weigh like a human does are, "How long will it take to get a CT scan? Does the patient's insurance cover an MRI? When is the next available rheumatology appointment? Can the patient take off time from work to get that thyroid scan? There are also patients' preferences that affect the diagnostic process: How aggressive does he want to be? How risk averse is she?"[53] These usually are not included as boxes in which providers can specify more comprehensive patient information to assist in diagnostics. As a result, Ofri's experiences depict the difficulties of actually putting AI into healthcare practices - most of which are overshadowed by the hope and hype of innovation.

[51] Ofri, Danielle. *When We Do Harm: A Doctor Confronts Medical Error*. Beacon Press, 2020.
[52] Ofri, Danielle. *When We Do Harm: A Doctor Confronts Medical Error*. Beacon Press, 2020.
[53] Ofri, Danielle. *When We Do Harm: A Doctor Confronts Medical Error*. Beacon Press, 2020.

Another complication of AI in healthcare emphasized through Ofri's experiences is the prospect of added technology negatively influencing the doctor-patient relationship. The U.S. healthcare system's fee-for-service model dramatically reduces the amount of time providers spend on each patient; they are paid more when they execute a greater number of appointments, tests, or treatments. In turn, they are not incentivized to take their time on individual cases to get to the root of a problem. If AI tools were added into that equation, their tendency to "[subtract] from the (already limited) direct face time between doctors and patients [would have] to offer proven value," considering "these systems take time to employ" and that the "doctor would have to stop [his or] her evaluation of the patient in order to give time to the algorithm."[54] This would require a complete culture shift in the healthcare industry, but supposing that AI technologies *were* utilized, it is ultimately not the responsibility of the computer to commit to a diagnosis, treatment plan, or prognosis. For the young woman evaluated by Ofri, the task of artificial intelligence to "simply [generate] a list of possibilities [wasn't] the same as making the diagnosis…Unlike a computerized algorithm, [Ofri's team] still had to do something to help her symptoms. [They] still had to commit, even in the absence of a specific diagnosis."[55] In the end, committing to a diagnosis meant analyzing several clues that a computer could not have picked up on: her improved breathing when outside of the new apartment. Although it was never confirmed that mold was causing the shortness of breath or that claustrophobia and anxiety triggered the rapid heart rate, doctors' final recommendation to merely decrease time spent inside the apartment likely prevented adherence to a diagnostic error and overtreatment. Ofri's commitment to helping the patient restructure her daily activities to spend more time away from

[54] Ofri, Danielle. *When We Do Harm: A Doctor Confronts Medical Error*. Beacon Press, 2020.
[55] Ofri, Danielle. *When We Do Harm: A Doctor Confronts Medical Error*. Beacon Press, 2020.

the apartment thereby strengthened the doctor-patient relationship, whereas the computer's risk of inducing unnecessary treatment upon the woman could have diminished that trust. The conclusion of this case exhibits one of the biggest advantages for training doctors over AI in healthcare: the doctor *can* capture the patient holistically and contextualize, while the machine struggles to do so. Accomplishing true artificial intelligence aligned with the definition established for this research would not negate machines' inability to show emotion, sympathy, and genuine interest in improving quality of life; it solely arrives at a quick diagnostic solution dependent upon the provider's inputs. Due to this insufficiency, artificial intelligence for healthcare practices could inhibit many positive doctor-patient relationships as well as accurate diagnoses - evidencing AI's notable difficulties in practice and the lack of conversation surrounding how AI might increasingly damage U.S. healthcare.

Chapter Four:

Barriers to Implementing AI in Healthcare

Overview

As previously noted, the United States remains a global leader in venture capital funding to healthcare AI, but despite the significance of that amount, foundational technologies dictating AI's success in the medical realm are still largely imperfect. Unlike Europe, the U.S. lacks an advanced national health system for accessing large amounts of health data, inhibiting much of the VC funding from contributing to meaningful AI experimentation. By this logic, AI cannot integrate into the U.S. healthcare industry without improving its understructure beforehand. Given that a primary objective for U.S. artificial intelligence is to assist in clinical decisions and for the machine to deliver personalized care, access to more health data like that of European healthcare systems is pivotal. To achieve this, high-quality electronic health records (EHRs) must first become a widespread reality. Thus, they represent the AI understructure. EHRs are the mechanism by which data is maintained for patients' laboratory results, summaries of care, provider visits, and medical history within an electronic system - yet physicians continue to struggle with “clunky interfaces and time-consuming data entry. Polls suggest that they [even] spend more time interacting with a patient’s file than with the actual patient.”[56] Unfortunately, this polling reflects areas where EHR utilization actually exists. In multiple parts of the United States, EHRs are still nonexistent. Promoting healthcare AI adoption will thereby require targeting U.S. states or regions where EHR use is comparably low. Failing to do so would inhibit the data sharing and integration across state borders that is necessary for AI. To comprehend the current status of data sharing and integration in the healthcare industry, this chapter explores the evolution of the electronic health record from the Obama Presidency to modern day. After reviewing literature on EHR perks and challenges, the paper completes its own study on electronic health record capabilities in the United States and compares the difficulties in practice from the perspective of Ofri.

President Obama and the Push for EHRs

In 2009, President Barack Obama led the initial push for EHR adoption, providing “$36 billion in financial incentives to drive hospitals and clinics to transition from paper charts to EHRs.” The shift was expected to “cut waste, eliminate red tape, and save lives by reducing the deadly but preventable medical errors that pervade our health care system.”[57] While EHR adoption certainly increased following the act’s passage, the technical challenges accompanying that increase led to unanticipated rates of provider burnout. Heightened by time-consuming data entry, these usability barriers continue to burden providers today. Not only that, but a 2018 report

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[56] Willyard, Cassandra. “Can AI Fix Medical Records?” *Nature News*, Nature Publishing Group, 18 Dec. 2019, www.nature.com/articles/d41586-019-03848-y#:~:text=Physicians%20complain%20about%20clunky%20interfaces,burnout%20is%20on%20the%20rise.

[57] Willyard, Cassandra. “Can AI Fix Medical Records?” *Nature News*, Nature Publishing Group, 18 Dec. 2019, www.nature.com/articles/d41586-019-03848-y#:~:text=Physicians%20complain%20about%20clunky%20interfaces,burnout%20is%20on%20the%20rise.

by the National Academy of Medicine found that EHRs still lack "'the ability to seamlessly and automatically deliver data when and where it is needed under a trusted network without political, technical, or financial blocking.' If a patient changes doctors, visits urgent care or moves across the country, records might or might not follow."[58] In turn, EHRs risk having insufficient patient data and, in these cases, are unprepared for use in AI algorithms. Facilities that currently have such systems in place cannot utilize them to their fullest potential until out-of-network or out-of-state providers also have systems that can collaborate with one another. On that account, EHR usability concerns and restrictions against sharing parts of its patient data must be confronted so that advanced AI technologies are not building upon fragmented systems. Improving the foundation of EHRs and their data sharing abilities must therefore be a priority - with a specific focus on integrating patient information from outside sources without needing to manually enter data.

Even though it was the federal government leading the multi-billion dollar campaign to push U.S. healthcare facilities toward adopting EHRs, the federal government, itself, remains cognizant of the shortcomings. Predominantly relating to interoperability, these shortcomings and underlying weaknesses of electronic health records certify that the current state of EHRs is insufficient for healthcare AI. The 2019 Roundtable on Sharing and Utilizing Health Data for AI Applications - led by the Center for Open Data Enterprise (CODE) and the U.S. Department of Health and Human Services (HHS) - summarized EHR data (classified under Clinical Data) as one of the "high-value health data types that can be used for AI development."[59] Its value stems from physicians' ability to use the EHR data in forming unique treatment plans and better

[58] Willyard, Cassandra. "Can AI Fix Medical Records?" *Nature News*, Nature Publishing Group, 18 Dec. 2019, www.nature.com/articles/d41586-019-03848-y#:~:text=Physicians%20complain%20about%20clunky%20interfaces,burnout%20is%20on%20the%20rise.

[59] "Sharing and Utilizing Health Data for AI Applications." *Home - Center for Open Data Enterprise*, Center for Open Data Enterprise, 16 Apr. 2019, www.opendataenterprise.org/publications.

diagnoses - as previously discussed in Chapter Three's proposed benefits of AI. The EHR data also serves a purpose on a population-level, enabling more studies for creating population profiles that combine data with social determinants of health. But despite notable EHR value in these regards, interoperability continues to inhibit electronic health records from making meaningful contributions. One of the primary goals of Obama's campaign was to "connect EHR systems so that physicians can easily share their patients' records with other providers regardless of the software being used," yet by 2015, "only 6% of health care providers could share patient data with other clinicians who use an EHR system different from their own."[60] This is at the fault of providers and vendors, who have both been "accused of 'information blocking' or intentionally interfering with the flow of information between different EHR systems."[61] For health systems and their providers, the motivation behind information blocking "was that by controlling patient referrals and having exclusive access to patient data, they could potentially improve their revenue and enhance their market dominance."[62] Similarly, EHR vendors had financial incentives to charge high fees for enabling "interfaces to connect to blood and pathology laboratories, hospitals, pharmacies, and other providers."[63] More recent legislation, including the 21st Century Cures Act, has certainly made the act of information blocking more punishable, but the multitude of data structures in various EHRs continue to challenge the

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[60] Reisman, Miriam. "EHRs: The Challenge of Making Electronic Data Usable and Interoperable." *P & T : a Peer-Reviewed Journal for Formulary Management*, MediMedia USA, Inc., Sept. 2017, www.ncbi.nlm.nih.gov/pmc/articles/PMC5565131/.

[61] Reisman, Miriam. "EHRs: The Challenge of Making Electronic Data Usable and Interoperable." *P & T : a Peer-Reviewed Journal for Formulary Management*, MediMedia USA, Inc., Sept. 2017, www.ncbi.nlm.nih.gov/pmc/articles/PMC5565131/.

[62] Reisman, Miriam. "EHRs: The Challenge of Making Electronic Data Usable and Interoperable." *P & T : a Peer-Reviewed Journal for Formulary Management*, MediMedia USA, Inc., Sept. 2017, www.ncbi.nlm.nih.gov/pmc/articles/PMC5565131/.

[63] Reisman, Miriam. "EHRs: The Challenge of Making Electronic Data Usable and Interoperable." *P & T : a Peer-Reviewed Journal for Formulary Management*, MediMedia USA, Inc., Sept. 2017, www.ncbi.nlm.nih.gov/pmc/articles/PMC5565131/.

exchange or joining of health datasets. That deficiency and the persistence of interoperability issues will increasingly hinder healthcare AI development and enactment.

Data on EHR Systems

To better understand the extent to which electronic health records pose a barrier for healthcare AI, this section takes a data-driven approach to uphold the findings of previous literature. More specifically, it performs its own data analysis on factors related to EHR utilization, usability, and interoperability in the United States - demonstrating the current state of EHRs and areas for improvement if AI is to be realized in the medical field. The American Hospital Association Annual Survey published through the Office of the National Coordinator for Health Information Technology (a division of the U.S. Department of Health and Human Services) publicizes information regarding health technology trends across hospital facilities. In collaboration with state healthcare agencies, Medicare and Medicaid centers, national organizations, and governmental bodies, over 6,200 hospitals are identified for the AHA survey each year - with an impressive response rate upwards of 75%. By selecting information from the survey relating to electronic health records, this section completes a cross-state comparison using 2015 data to examine which states or regions are the most prepared for AI in healthcare. Since the data is several years old, it may seem as if the numbers are outdated or misrepresentative of current trends. However, using this past survey data is actually quite practical due to the prolonged transition periods to new EHR systems. In fact, one rehabilitation facility in upstate New York commented that, in addition to their EHR transition being put off for a year due to the COVID-19 pandemic, vital signs and other important health conditions would still have to be manually transferred from the old system into the new EHR system - a process that will take years to get all patients set up in. Given that EHR updates and changes are not typically quick fixes but rather take years to implement, 2015 data remains relevant. Accordingly, the four guiding questions for analyzing the 2015 AHA survey data are:

1. Does the prevalence of electronic health records in hospitals differ by region? In other words, are certain regions more technologically advanced in the healthcare industry than others?
2. To what extent are electronic health records utilized in each region? Are some hospitals able to do more with their EHRs than others?
3. With electronic health records in place, what is the relationship between hospitals and providers outside of their network?
4. Considering the responses to Questions 1-3 indicated by the data, is there a sufficient foundation for artificial intelligence to be utilized in the healthcare industry?

Insights from these guiding questions are derived by coding the selected AHA survey data into a map and heatmap using Google's Colaboratory Notebook tool. The analysis finds that while connected care is the goal, disconnected care is the reality in the U.S. healthcare system. EHRs are essentially libraries for patient data that could assist in AI development, but they are not set up to enable the simple data sharing necessary for much of AI's proposed industry changes. Thus, the use of AI to benefit healthcare cannot be effective until electronic health records can collectively find, send, receive, and integrate patient data on a national scale. The visuals from which these insights arise are shown below and discussed in the next subsection.

Results of Coded Map and Heatmap

Evaluating the technology incorporated into medical facilities on both a national and regional level are indispensable steps toward realizing the state of AI preparation in the U.S. healthcare industry. Figure 4.1 offers an initial overview of the foundational technologies' presence in the U.S. for AI to be successful. Specifically, the map looks at the percent of all non-federal acute care hospitals in the country that have adopted at least a basic electronic health record system with clinician notes. The map is shaded by state according to the cumulative existence of these EHRs. Lighter shades indicate fewer hospitals in the state with a basic EHR, while darker shades indicate a greater number of hospitals in the state with a basic EHR. Based upon these measures, the coded map suggests that at least 65% of hospitals in each state have adopted at least a basic EHR. Snippets of code printed in Figures 4.1.1 and 4.1.2 from the corresponding Google Colaboratory Notebook in which these visuals were executed confirm that it was Vermont ranking the lowest with that 65% and Maryland boasting the highest percentage of hospitals with basic EHR systems at 95%. Other states with lower basic EHR adoption were Delaware at 67%, Louisiana and Rhode Island each at 70%, and Hawaii at 71%. States with higher basic EHR adoption included Nevada, Washington, and Wyoming all at 94%, Massachusetts, Utah, and Virginia all at 93%, and Arkansas at 90%.

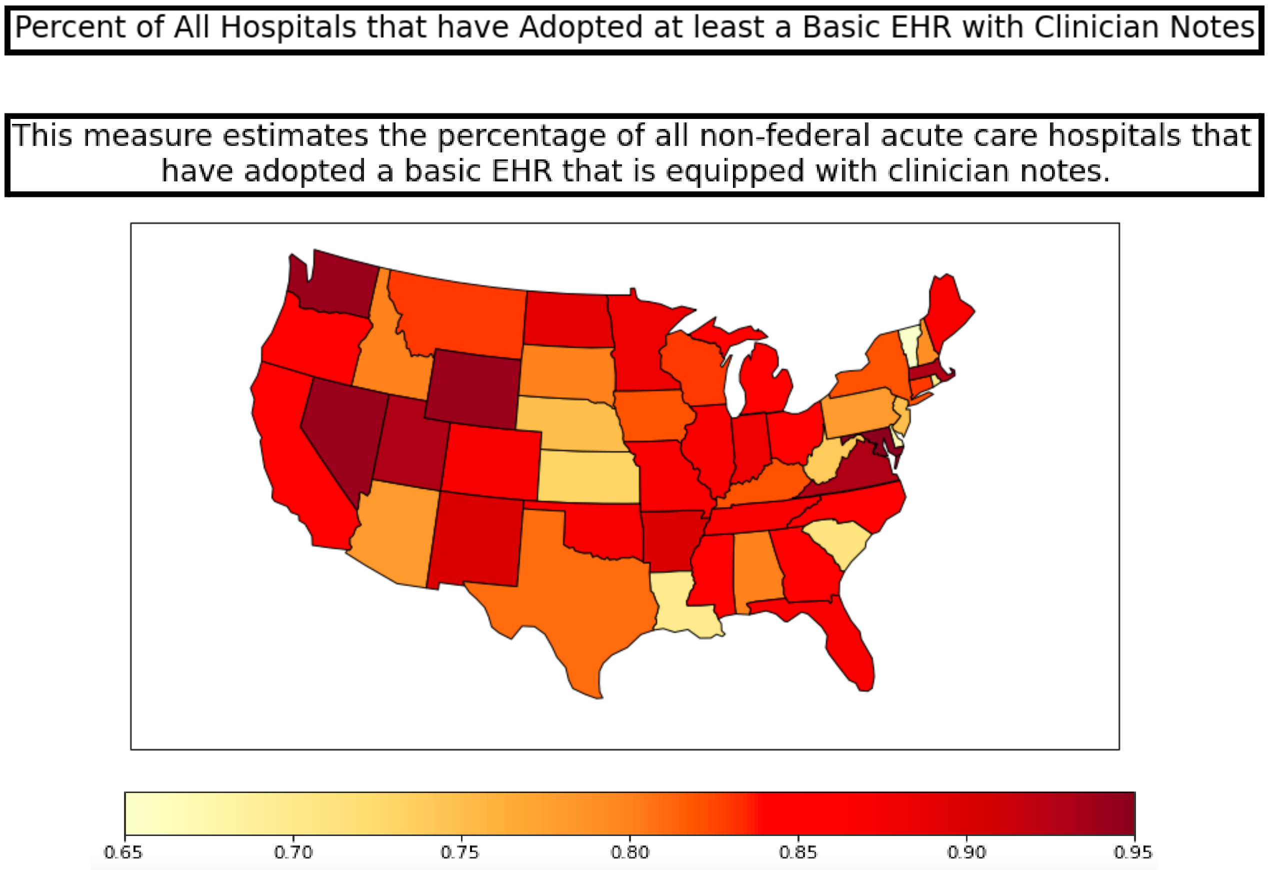

Figure 4.1: Map of U.S. Hospitals with Basic EHR
Source: American Hospital Association Annual Survey

```
period.nsmallest(5, 'pct_hospitals_basic_ehr_notes')
```

	region	region_code	period	pct_hospitals_basic_ehr_notes
99	Vermont	VT	2015	0.65
61	Delaware	DE	2015	0.67
71	Louisiana	LA	2015	0.70
92	Rhode Island	RI	2015	0.70
64	Hawaii	HI	2015	0.71

Code 4.1.1: States with Smallest Percentage of Hospitals with Basic EHR
Source: Bonnist Colaboratory Notebook

```
period.nlargest(8, 'pct_hospitals_basic_ehr_notes')
```

	region	region_code	period	pct_hospitals_basic_ehr_notes
73	Maryland	MD	2015	0.95
86	Nevada	NV	2015	0.94
100	Washington	WA	2015	0.94
103	Wyoming	WY	2015	0.94
72	Massachusetts	MA	2015	0.93
97	Utah	UT	2015	0.93
98	Virginia	VA	2015	0.93
55	Arkansas	AR	2015	0.90

Code 4.1.2: States with Largest Percentage of Hospitals with Basic EHR
Source: Bonnist Google Colaboratory Notebook

In consideration of these statistics, there was no consistent or notable pattern in terms of location in the United States and the extent of basic EHR adoption. Thus, Figure 4.2 was coded to take a closer look into hospitals' electronic capabilities with clinical information from EHRs by region. The particular measures used in the figure are the estimated percentages of hospitals by respective region that can electronically find, send, and receive patient summary of care records from sources outside their own organization. It also measures the estimated percentages of hospitals that can integrate patient information received electronically from outside sources without needing to manually enter the data. As evidenced by the heatmap's shading - which is colored in the same manner as the U.S. map from Figure 4.1 - hospitals were more likely to be able to send and receive clinical information but less likely to be able to find and integrate clinical information. These trends were the same in every region. The capacity to find clinical information ranged from 46.3% in the South to 59.8% in the West. The capacity to send clinical information ranged from 81.8% in the Midwest to 89% in both the Northeast and South. The capacity to receive clinical information ranged from 65.2% in the Midwest to 71.7% in the South. Lastly, the capacity to integrate clinical information ranged from 50% in the Northeast to 53.3% in the South. The significance behind these values from the U.S. map and regional heatmap are further explored in the following section.

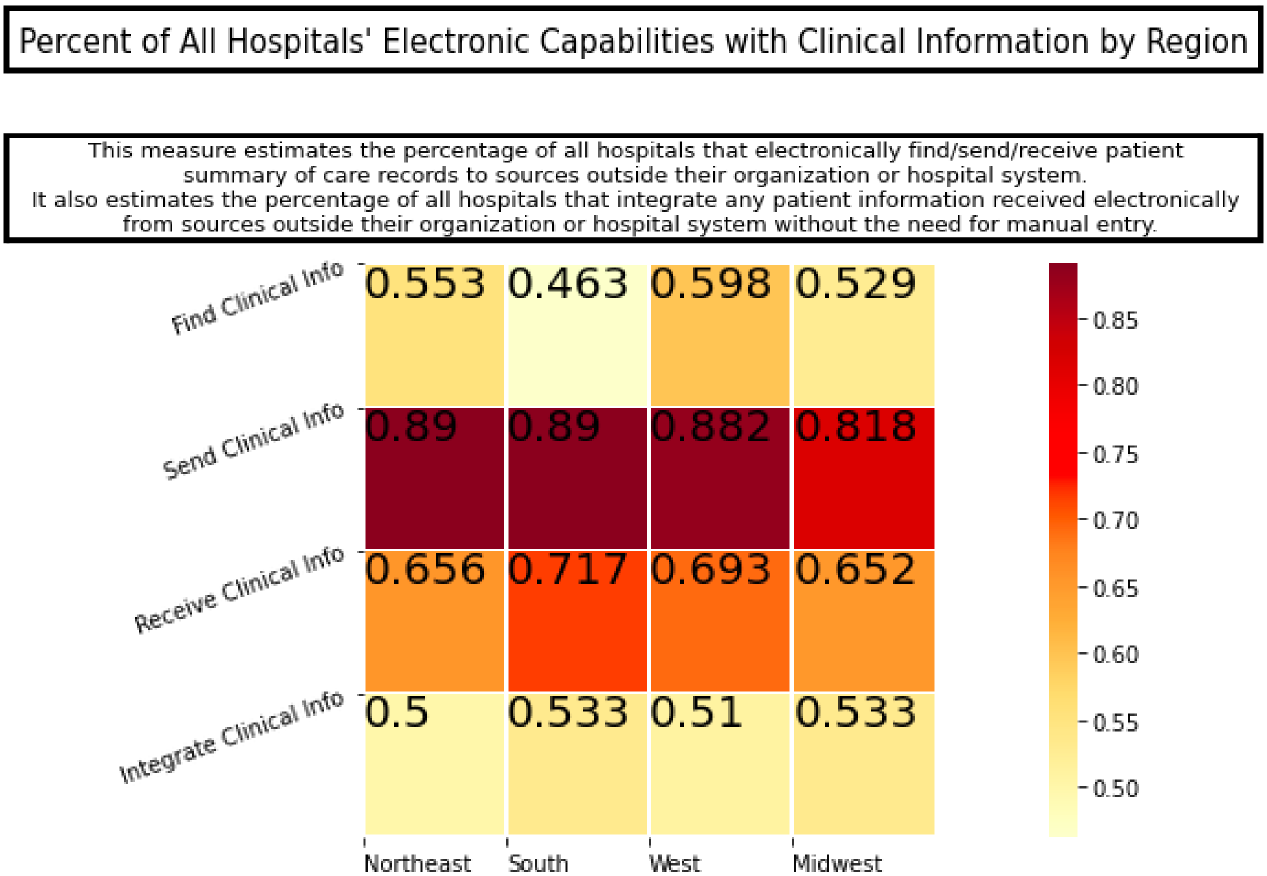

Figure 4.2: Heatmap of U.S. Hospitals Electronic Capabilities by Region
Source: American Hospital Association Annual Survey

Insights into the State of EHRs

Overall, both visualizations depict how the use of AI to benefit healthcare cannot be effective until electronic health records are widely utilized to find, send, receive, and integrate patient data across states and regions. Hospitals that *do* have proper systems in place cannot utilize them to their fullest potential until providers beyond their network and state have systems that can easily collaborate. Though the estimated percent of all hospitals using EHRs to exchange summary care records with any outside providers did not drastically differ by region based upon the U.S. map, what *did* differ was the distribution of the data. In assessing the raw AHA survey datapoints, it became apparent that the Northeast, South, and Midwest had relatively small distributions - meaning that there was less variability in the regions' percentages denoting their hospitals' ability to exchange summary care records with outside providers. On the other hand, the West had a larger distribution and therefore more variability. This ultimately implies that most hospitals within the Northeast, South, and Midwest regions have similar capabilities with clinical information, yet some Western hospitals are notably more advanced than other Western hospitals. As a result, future development of EHRs must appreciably focus on the regions with larger distributions to revamp hospitals within lower quartiles. More specifically, attention to integrating patient information from outside sources without needing to manually enter data should be a top initiative. So long as states have numerous hospitals without proper EHRs in place for exchanging summary care records or finding, sending, receiving, and integrating clinical information from outside providers, the U.S. healthcare system will not achieve the level of connected care necessary for AI to ever thrive in a medical setting. Because of this, outdated EHRs and the persistent inability for systems to collaborate with one another pose the greatest barrier to achieving AI in healthcare.

More Difficulties in Practice: A Doctor's Perspective

In this section, the experiences of Dr. Danielle Ofri are relayed once again to determine how electronic health records in practice add several difficulties to daily routines and interactions with patients. Her stories validate the concept of EHRs as foundational technologies being unprepared for artificial intelligence. Among the main issues Ofri has with the electronic health record is that it "has fundamentally changed how health professionals process medical information. When [she] opens up the [EHR], the computer forces [her] to document in its order, which has no relationship to the arc of [her] thoughts. Even the best of the [EHRs] do not think the way clinicians think. Humans must be rerouted to the [EHR's] requirements."[64] When the provider's train of thought is interrupted by the computer's demands to compartmentalize, all of the factors influencing a patient's health are not accounted for comprehensively, which can result in errors such as misdiagnosing. The EHR's requirement for compartmentalizing also makes the process of finding, sending, receiving, and integrating clinical information - such as the summary of care records analyzed in Figure 4.2 - less attainable. Ofri notes that, when healthcare was still dominated by paper and not the computer, she "could group the blood test results and the X-ray results together because they logically formed supporting data to prove or disprove a diagnosis. But in the [EHR], the lab results are in one place, and the radiology results in another, and the consultations are in a third place."[65] Given the extent to which Ofri feels this fragments her thinking as she uses that hospital's system, the additional efforts that would be required of her and her colleagues to then achieve interoperability and the exchange of data with other EHR systems feels quite far-fetched at the moment. This manifests electronic health records' unpreparedness for incorporation into AI tools.

Furthermore, Ofri narrates how her experiences with the electronic health record reflect healthcare facilities' greater concern with liability than patient safety. If patient safety is still

[64] Ofri, Danielle. *When We Do Harm: A Doctor Confronts Medical Error*. Beacon Press, 2020.
[65] Ofri, Danielle. *When We Do Harm: A Doctor Confronts Medical Error*. Beacon Press, 2020.

under-prioritized in EHR systems, the assertion that AI will aid clinician care teams to ensure patient safety feels premature. If patient safety is still flawed in the EHR, it may be naive to assume that a more advanced tool using artificial intelligence and methods partially concealed from the human eye (refer to Chapter Two for more details on this framework) is the mechanism to finally guarantee it. This highlights the idea of foundational technologies requiring attention prior to complex AI additions. Ofri remembers one daunting case in which an error lost in the electronic health record led to disaster. When prescribing the antibiotic Bactrim to a pediatric patient, a resident in the hospital went to enter the dose into their EHR - which had the options for standard milligram dosing or weight-based dosing. The EHR defaulted to mg/kg units, which had been the previous measurement used in the system for another patient, but the resident had meant to select weight-based dosing. This resulted in grossly over-calculating the dosage. Without realizing that the EHR had defaulted to the improper measurement, the resident confirmed the dose and a nurse was sent to administer the pills to the patient. Because the facility was an academic medical center and frequently did experimental treatments, the nurse did not question the atypical dosing - especially given that the order had been double-checked by the resident and pharmacist. Shortly after receiving the pills, the patient had full-body seizures - which could have caused permanent brain damage in a worst-case scenario. Although the patient recovered, the experience demonstrated the potentially fatal flaw of the EHR: a system "that is trying to improve patient safety through its various alerts and warnings can instead end up harming a patient gravely. It's all the more ironic because this is an error that would have been caught in a flash if the doctor had written the order by hand instead of computer."[66]

[66] Ofri, Danielle. *When We Do Harm: A Doctor Confronts Medical Error*. Beacon Press, 2020.

What is more, the countless alerts and warnings feel like a transfer of blame to providers like Ofri in the case that something goes wrong. She admits, “It’s so clear to us that the first priority is attending to liability rather than to patient care. If they’ve posted every possible warning, no matter how lame, then they - the hospital, the [EHR], the greater universe - cannot be held at fault if something goes wrong. It’s the doctor who clicked ‘okay’ to the warnings who is at fault.” This reality calls into question the true purposes behind supposed safety measures in the EHR and whether it is the patient or hospital as a profitable business being protected with these pop-ups. Hence, the unfavorable usability of electronic health records poses a major barrier to the success of healthcare. Providers are continuing to burn out, as was the case following the introduction of Obama’s EHR adoption campaign, and EHR designs causing more error have negative impacts on all parties in the healthcare industry - from clinician care teams and patients to public health program managers and business administrators; their success is all interconnected. Adding artificial intelligence into that equation would require providers to get acquainted with entirely new technologies. Doing so would overlook the need to address incompatibility between providers and EHRs before attempting any further technological advancements in medical operations.

Chapter Five:

Discussion and Conclusion

Summary of Research

Overall, this research has outlined the prominent topics of discussion relating to the future of artificial intelligence in the healthcare industry. Chapter One introduced the notion of AI ushering society as we know it into a new phase of discovery, but because historians of technological advancement tend to capture the excitement of the people in response to the potential for innovation, the chapter warns against assuming AI to be a "given" or an inevitable innovation. It advises individuals to analyze history in a holistic manner to consider the choices we were faced with at the prospect of new technologies in the past and ultimately whether those technologies were the appropriate solution to that facet of life. Maintaining this approach for modern day choices is crucial given the narrative dominating AI. It is being portrayed as the leading mechanism to better health, while other choices for systemic improvements are becoming overshadowed by the "spirit of the people."

With the narrative surrounding AI falsely depicting the extent of artificial intelligence in the United States, Chapter Two clarifies the discrepancies in literature by differentiating what constitutes computer knowledge, machine learning, deep learning, and artificial intelligence. The key distinguisher between these applications is how learning occurs. Knowledge is merely the transfer of information from a human to the computer - as demonstrated by a human coding Rule 543 of MYCIN based upon information provided from doctors. Machine learning is more advanced than computer knowledge in the sense that the computer learns on its own without human intervention; this is accomplished through pattern detection in data. Furthermore, deep learning is explained as a subfield of machine learning with the power to predict which inputs (such as images of tumors) belong to which categories (such as benign or malignant). Deep learning also has the capacity to test its accuracy in these predictions. Clarifying these various applications thereby made the concept of artificial intelligence clearer. The key difference between artificial intelligence and the aforementioned tools is that true AI would have a sense of the real world, whereas the other tools would not. As of now, computers do not exhibit these critical thinking skills - hence why this research argues that the “AI” historians and journalists optimistically portray does not yet exist. Rather, techniques such as machine learning have become mistaken for artificial intelligence as our standards for what we want out of technology rises. This has dangerous implications for the healthcare industry - a field constantly up against liability and ethical concerns.

Next, Chapter Three used the clarified definition from Chapter Two to analyze the proposed benefits of healthcare AI versus the difficulties of putting it into practice from the perspective of providers. A specific focus is placed upon clinician care teams as a case group projected to reap these benefits. The first category of potential AI benefits for clinician care teams was early detection, prediction, and diagnostic tools. The second category was surgical procedures, the third category was precision medicine, and the final category was patient safety. The paper considered how successfully achieving AI for those proposed categories under clinician care teams would, in turn, positively impact other user groups - especially patients and their families. However, the perspective of Dr. Danielle Ofri on utilizing artificial intelligence told a conflicting story - as the technology often made matters unnecessarily complicated or took a vastly different approach than a human doctor ever would in making diagnoses. This suggested a lack of conversation surrounding how AI could actually damage aspects of healthcare.

Lastly, Chapter Four presented its own empirical examination of the greatest barrier to implementing AI in healthcare: inadequate electronic health records. EHRs offer vast troves of patient data, which is crucial for the development of artificial intelligence and its algorithms. However, the systems are largely unprepared for this role at the moment. Following a brief overview of the Obama Administration and their push for widespread EHR adoption, the chapter used 2015 survey data from the American Hospital Association to get a better sense of current EHR capabilities on both a national and regional scale. Results were then coded into a map and heatmap - subsequently revealing the consistent inability for different EHR systems to collaborate with one another as well as the usability flaws within a system, itself. This prevents the level of connected care desired. Thus, Ofri's experiences with electronic health records were relayed and affirmed that AI cannot be realized in the medical field's future without significant attention paid to EHR deficiencies at present.

Discussion and Conclusion

Considering all findings of this research, it is evident that the future of artificial intelligence within the healthcare industry and beyond remains uncertain. Still, it is worth revisiting the holistic questions discussed in Chapter One for analyzing prior technological eras and applying those inquiries to modern day. This leads us to ponder the potential choices we may be presented with in the future as new innovations surface, just as this has occurred throughout history. For example, we must contemplate, “How do new technologies establish themselves in society, and how does society adapt to them?” Undoubtedly, industrialization replacing traditionally human-led jobs has brought about controversy many times before, but the notion of artificial intelligence one day achieving a real sense of the world or critical thinking skills is a concept unlike anything mankind has ever known. Although historians and journalists alike may continue to promote the “spirit of the people” above the drawbacks of artificial intelligence and the choices we still have for how, where, or whether to even use it, this paper finds that the United States cannot assert AI as its future for the healthcare industry. Rather, current discussions surrounding AI must center on how technological innovations can support providers and their teams in daily practices - not replace them. Failing to engage in these types of conversations will dismiss other viable options to revitalize the healthcare industry and overlook the necessity to address major issues in foundational technologies - especially the electronic health record. This ultimately illustrates that devoting time and resources to healthcare AI while the industry’s foundation is left fragmented would be a disservice to all involved parties and inhibit improvements to the system as a whole.

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