The Future of the Healthcare Industry: How Information, Technology and Consumerism Will Pave the Way

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Abstract

The application of data science has been growing within the healthcare industry via hospitals, as well as pharmaceutical and technology companies. In recent decades, healthcare delivery has progressed towards using computer assisted methods. These methods are applied through the tools of data science, which have greatly improved healthcare providers abilities in their evidence-based decision making. Data science renders a standardized and automated capability for data analysis that research has shown to be highly effective. A major application of data science is machine learning, which uses computer coding, such as Python, and algorithms to solve problems. Its use has shown great success within healthcare management, clinical administration, and clinical practice. Further, it has become popularized to advance consumerism with a potential to cause positive economic effects. Going forward, data science should be implemented to improve healthcare delivery. Regarding public health, data science is important to effectively utilize data to draw connections to create an improved understand and more informed decisions.

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1.0 Introduction

Any growing healthcare organization should have a strong focus on their data and comprehension of how to best optimize it. With the exponential development of information and technology that has been growing within healthcare more quickly than other industries, healthcare delivery has transitioned into a data driven and analytical arena that employs advanced technologies to reach its aims. These technologies have included those such as machine learning which have applied data science to solve for a diverse range of problems. Data science bolsters healthcare delivery organizations to be more quantitative, evidence-based, and objective while advancing their operations as they better care for their patients. Beneficially, data science takes traditionally time exhausting tasks such as data concatenation, entry, manipulation, and wrangling and standardizes and automates the process. Upon doing this at much quicker speeds and, oftentimes, with more accuracy than people, it can further review the data to draw conclusions.

This paper will examine how data science can be utilized to improve healthcare delivery and enhance consumerism. Data science can do this using technology assisted algorithms to accommodate decision making for healthcare delivery managers and clinicians. These accommodations are employed for strengthening readmission and length of stay metrics, the revenue cycle, data collection and use, diagnostics, and prognostics. Regarding consumerism, data science can be implemented within the hospital and remote settings. Although the research is inconclusive, data science also has the prospect to financially improve healthcare delivery.

2.0 Data Science

Data science will be one of the largest stimulants to the healthcare industry and assist in the standardization and automation of data. It is a broad topic that can be broken down into three parts: math and statistics, computer science, and a domain such as healthcare, business, or finance. The math and statistics used are to compute the quantitative analysis. Computer science is primarily used in data science within the context of artificial intelligence. Briefly speaking, artificial intelligence is the ability of computers to process data to make independent decisions. Computer science takes the math and statistics and integrates it into a language so a computer can read it. This is completed via coding. Simply, domain is the keyword for data science that means area of concentration. Math and statistics, as well as computer science can be applied to an unlimited range of topics, and the domain is just the field of application. Within healthcare, data science will move technology from primarily just collecting and presenting data to being able to methodically analyze data to ultimately inform provider and consumer decisions.

2.1 Programming Libraries

The most used computer programming language for data science is Python. Outside of the foundational Python language, many programming libraries have been developed that use Python coding for specific tasks. For example, Numpy and Pandas are two of the more essential and commonly used libraries that allow Python to be used in a more robust manner. Numpy is for working with numbers and Pandas is for working with data analysis. Although these libraries are not particular to any major data science initiatives, they are important because so many of these initiatives are driven through their need for computing with numbers and manipulating data. More specialized libraries include Matplotlib for data visualization, Kivy and Tkinter for graphic user interfaces, TensorFlow and Scikit-learn for machine learning, Keras and Theano for neural networks, and Pytorch for natural language processing (NLP). Overall, Python is used within healthcare using data science models such as clustering, Gaussian, K-means, K-nearest neighbors, support vector machine, regression, and Bayesian to find solutions to machine learning based problems (Dua, 2016). It is a programming language that uses these models as tools to answer different types of questions.

Many of these libraries may be the best for certain tasks but they also have crossover between such tasks. For example, even though Pytorch is very popular in NLP, it can also be used for more generalized machine learning tasks. Additionally, although a library may be the best for a task in a general sense, such as machine learning, some are built to handle more technical parts of each tasks, such as unsupervised machine learning. Interestingly, people interact with some of these libraries on a regular basis and do not know. For instance, Google, who developed TensorFlow, uses it to determine which of their Gmail user's emails may be spam.

2.2 Electronic Health Records

The use of traditional data analytics is very common in healthcare, but there is room for improvement. Over the past decade, much of this analysis has been completed using EHRs. For example, 68% of hospitals use EHRs to develop dashboards for their organizational data and 57% for their smaller divisions, such as their departments (Gasoyan, 2020). Machine learning could bring this data analysis into the new era of the digital frontier with a higher volume, frequency, variety, and level of processing of data. Healthcare data comes from a large breadth of sources across different areas such as clinical, administrative, and population data. These data sources include clinical notes, prescription history, insurance coverage, demographics, testing, and scans. Due to the complexity of this data, healthcare data is an ideal candidate for use in data science. Since, for quantitative tasks, human processing capabilities are in many ways more limited than that of computer systems, data science can help to fully realize the potential of data and deduce conclusions that may not be possible without computational assistance.

2.3 Increases in the Volume of Data

The healthcare industry's frequency of producing new data has been growing faster than other large industries. The amount of data is expected to grow five-fold between 2019 and 2025. Although, the least common data types are those for data analysis and artificial intelligence. Further, healthcare is held back through having an inadequate investment into information technology (IT) across all areas, which causes issues such as poor data management and cybersecurity (Reinsel, 2018). If data science is going to be properly implemented, these problem areas will need to be cogently addressed. To manage the data, a query language such as SQL may be used to manipulate and retrieve stored data. To ensure the fast and proficient processing of the data, software such as Hadoop and Apache can be used. These data management and processing tools enable programming languages to analyze data most effectively. Essentially, they all work together like a set of tools that can be used for data science initiatives.

3.0 Machine Learning

Machine learning is useful for running algorithms to discover relationships between variables that are unknown or very complex to find without the use of computer technology. It is an application of data science and used to teach computers to learn through their experience based on pattern recognition. Currently accessible machine learning falls into the category of *narrow* artificial intelligence, as opposed to *general* artificial intelligence. This means that it is capable of a narrow set of specified tasks such a pattern recognition. General artificial intelligence simulates human thinking which is characterized through high-level traits such as abstract and emotion-based decision making.

Machine learning can be broken down into three different types: supervised, unsupervised, and reinforcement learning. Supervised learning uses labeled data, where unsupervised learning uses unlabeled data. Supervised learning can be used for techniques such as classification and regression, and unsupervised learning can be used for cluster analysis and dimension reduction. Reinforcement learning is when an agent interacts with its environment and learns how to navigate it through trial and error via punishments and rewards. Within machine learning research for healthcare, the most popular data science models have been neural networks and support vector machine (Jiang, 2017).

3.1 Artificial Neural Networks

Often referred to in the shorthand as neural networks, artificial neural networks (ANN) are a subset of machine learning that has been aptly named because of its resemblance to a brain's network of neural cells. Work related to ANN were first published in 1988 and has since been applied to many different industries. Regarding healthcare, they have been very useful in diagnostics over the past two decades. For instance, ANN have been developed to diagnose a wide array of diseases including different types of cancer, gynecological, pancreatic and cardiological diseases, as well as multiple sclerosis, and diabetes (López-Rodríguez, 2013).

Simply, ANN is composed of interconnected neurons, which are also called nodes. It works through *forward propagation* when an input (ie: symptoms, blood tests, scans, and patient information) is multiplied by its weight and then added to a bias. The result of this is then sent through a series of *hidden* layers where it is processed through an algorithm called an *activation function*. Each neuron within the hidden layer analyzes a unique feature, and the ANN works to amalgamate this analysis from each neuron to draw a conclusion. Before an ANN can be used, it needs to be trained through data sets. When an ANN begins its training, it applies random weights and biases because it does not know how to accurately classify its inputs. Upon completing its forward propagation, it determines its error rate and delta (difference between the accurate and incorrect answer). Using *back propagation*, the ANN then flows backwards correcting its initial weights and biases. After each cycle of the forward and back propagation, the ANN progressively learns how to most accurately predict how to decipher an input.

3.2 Support Vector Machine

Support vector machine (SVM) is a data science model used to discern the categories between two different classes of items. A SVM model works with data that can be mapped on coordinates and can work with data anywhere from a one-dimensional to the infinite n^{th} dimensional plane. To properly classify data into categories, it utilizes three lines of separation called *decision boundaries*. The first line, called a *hyperplane,* is drawn between the two classes at the angle that leaves the widest margin of space between the two. Next, the remaining two lines, called *support vectors*, are drawn as close as possible to the different classes. Each of these lines is drawn close to only one of the classes. If a new data point is difficult to classify, it may fall within the area between the vector lines. Due to the imperfect nature of the SVM, this is expected, and these data points are considered errors. To minimize the rate of error, a C-parameter can be used. With a high C-parameter, the hyperplane can be moved, and the margins can become thinner. Although this reduces the rate of error, if the C-parameter is too high, it can overfit the model rendering it less accurate over time as new data is input. Lastly, in a situation where a one-dimensional plane is used and the data of one class is surrounded by a ring of the other class, a kernel function should be used to manipulate the data into a multi-dimensional plane.

3.3 Borrowing from Other Industries into Healthcare

Borrowing from the popular applications of machine learning in other areas of business such as e-commerce and online based technology, the healthcare industry can develop their own industry-suited technologies. In e-commerce, companies use machine learning to predict what a buyer may be interested in purchasing in the future based on their past purchase and product viewing history. For an example of an online based technology company, Google is used as a great example. Google follows a similar model through their web search engine, where they track each user's activity to determine what they tend to search and view online. Through this they can help their search users more quickly find what they are searching for. Essentially, the methods of these two sectors profile their users so the companies can generate a personalized experience that streamlines to them what they want.

4.0 Data Science Applications in Healthcare

4.1 Administrative Management

It is the healthcare administrator's duty to ensure that their organization runs efficiently on the backend so clinicians can focus on providing optimal care to the patients. To do this, it is essential for the administrators to use the best tools available to them. Advancements in tools for data science give a major edge and can be used in healthcare management for a variety of purposes such as decision support and revenue cycle. As healthcare providers have become more reliant on EHRs, as opposed to written medical records, the records have had a heightened transferability and usability. This has further opened an environment where healthcare managers can more comfortably apply data science techniques like data mining within big data to improve industry performance.

A promising machine learning model has been developed by Google and has been shown to have accurate predictions towards 30-day unplanned readmissions and prolonged length of stays. In fact, their model has outperformed other predictive models for such metrics (Rajkomar, 2018). Other machine learning models have also shown success within the ICU for predicting these readmissions. The application of these models can be used to identify patients who are at-risk for irregular stays so they can be targeted with more of a focus in how they are cared for. Since 2012 hospitals have been fined for excessive 30-day readmission rates for Medicare beneficiaries. The frequency of these fines has been significantly increasing since their implementation. For example, 2018 had $564 million in fines, which was a $144 million increase from 2016. This is nearly a

35% increase in just two years (Lin, 2019). Hospital managers could use machine learning models to their advantage to limit these fines.

Research into the effectiveness of machine learning has been very limited regarding the revenue cycle. Although, based on the success of machine learning in other areas of healthcare, it does carry great potential. For example, a lot of time is spent by physicians in the ambulatory setting completing prior authorizations. The American Medical Association conducted a survey of physicians and their opinions on prior authorizations and found that 48% stated that they at least often delay care, 86% stated its process is burdensome, and 86% stated that these burdens have increased over the past five years. The survey also found that, on average, each physician, sometimes with assistance from their staff, complete 33 prior authorizations a week and this takes them 14.4 hours (American Medical Association, 2019). If machine learning was applied to this area of healthcare, a lot of time could be saved.

4.2 Clinical Administration

About 50% of a clinician's workday is spent in the EHR. Of that time, 44.2% is consumed by clerical and administrative tasks such as documentation, order entry, billing and coding, and system security (Arndt, 2017). Further, with 74.5% of physicians listing their work with EHRs as a cause of physician burnout, the utilization of EHRs should be examined with serious consideration (Tajirian, 2020). The newly burgeoning company Olive has developed machine learning software algorithms to automatically handle time consuming, tedious administrative tasks. As of 2019, their algorithm has been implemented into over 500 hospitals and has already completed a vast amount of work. For example, they have accomplished approximately 350 million tasks. Of that, they have completed over 450,000 claims status checks for a hospital with more than 2,000 beds. Additionally, for a similarly sized hospital, they have completed over 250,000 billing corrections (Globe Newswire, 2019).

To assist clinicians in their clinical tasks, Amazon has developed a HIPAA compliant Alexa which allows them to use natural language processing (NLP) technology. NLP programs computers to be able to comprehend human language. This means that a computer will be able to scan written documents and transmit it into a format that a user can utilize while interacting with an EHR. Additionally, computers will be able to hear spoken word and transfer it for the same purposes. For instance, with this technology, clinicians can verbally speak into the Alexa to update medical records quickly and effectively.

4.3 Clinical Practice

In the clinical setting, data science can be used to assist in the diagnostic and prognostic process. Although medical errors are not the only area where data science can be applied, medical errors exemplify an area where it can discover great application. Medical errors are a serious issue within healthcare being that they are the third most common cause of death in the United States (Anderson, 2017). They are primarily the result of human error- rather than system error- which shines light on where quality improvement strategies can focus to reduce the rate of medical error (Fabri, 2008). About 75% of diagnostic errors were the cause of human error and exceed other types of medical errors by two to four times as much. Additionally, they make up approximately 40% of all ambulatory malpractice claims (Dilsizian, 2013). Due to the nature of computer-based functions, they are not capable of such errors. If properly engineered and maintained, they can compute data to formulate information that is not at risk for human errors such as overlooking details or misinterpreting data. Any given care scenario runs a risk for medical error. Data science is a tool that can be used to limit that risk while providing early advisory input towards clinical decisions. Regarding diagnostics, data science can determine a diagnosis before or after a disease's onset. Using that information, it can then proceed to recommend a care treatment plan. Further, data science has proven its application across a wide spectrum of clinical areas.

Sepsis is a bacterially induced disease that is prone to misdiagnosis since it is difficult to detect being that its symptoms mimic those of so many other diseases. This misdiagnosis can be fatal because over 30% of people with sepsis die (Soong, 2012). Further, it is the leading cause of death for in-hospital patients and a common cause of death for infants in the US (Rudd, 2020; Kochanek, 2020). Not only is this disease deadly, but it is imperative to catch it early because of how quickly it can cause septic shock, which rapidly progresses the disease. These features of sepsis lend it to be an excellent disease for machine learning to be applied. Fortunately, machine learning has been shown to detect it earlier and with an improved predictability for adults and children than physicians (Masino, 2019; Nemati, 2018). Looking forward, the further use of machine learning could strongly decrease the mortality rate and longevity of hospital stays from sepsis.

Another difficult disease to diagnose is retinopathy of prematurity (ROP). It is an eye disease caused from retina vessel abnormalities that is globally the primary cause of blindness in children. Through the training of a machine learning algorithm using 5,511 retinal photographs, the algorithm was able to learn how to diagnose the disease at a 91% accuracy rate, where expert ophthalmologists had an 82% accuracy rate (Brown, 2018). Research has also shown machine learning to be effective in other areas of healthcare. It has been able to review radiological scans to accurately diagnose pulmonary cancer (Setio, 2016). Researchers from Mt. Sinai have developed machine learning algorithms that correctly diagnose COVID-19 from patient CT scans and medical data at a rate that is significantly higher than physicians (Mei, 2020). Additionally, ANNs have been developed that have shown an equal accuracy in predicting skin cancer when compared to Dermatologist (Esteva, 2017).

Being that machine learning promotes predictive measures, it can enable the healthcare industry to be more proactive than reactive in their care. Also, depending on when it is used, it can find diagnoses earlier in the care process, which may catch diseases before they are intensified or irreversible. Further, these measures can be quantified for population level disease profiling. Machine learning's capabilities to handle large volumes of data at once provides it with the opportunity to draw connections along the care pathway to assist in individual patient care that can be extrapolated to entire populations.

Famous for its characteristic display of computing power on the television show *Jeopardy*, IBM's Watson can process approximately one-million books in the matter of a second. Since its television appearance, Watson has been programmed to review healthcare data and curate decisions. Essentially, Watson can analyze every available resource such as peer-reviewed research as well as patient records it is connected to and use that data to propose conclusions. This technology can be used through the entirety of the clinical process. It can review patient records to decide what testing and scans need to be completed, interpretate their results, and recommend diagnoses and prognoses (Dilsizian, 2013). Conclusively, this technology could be used to assist in clinical determinations at a rate far great than is humanly possible. This could provide clinicians with a higher turnaround rate per patient, which may allow them to see more patients or spend more time with each patient. Additionally, it could limit the number of inappropriate testing and scans issued.

5.0 Consumerism

Albeit all the aforementioned areas are excellent advancements on their own, they can be used together and readily applied to invigorate a move towards consumerism. A market shift that focuses chiefly on the consumer has placed the patient at the center of the provider's objectives. This includes the creation of an environment where the patient has easy access to information, control over their healthcare decisions, quality care, and options for care that adhere to their preferences. In association with data science, a patient-centered focus can be executed within and outside the bounds of the hospital. Within the hospital, data science can be utilized to drive informed and valuable care for the patient. Remotely, data science can be used alongside technology so patients can receive quality healthcare from the home or on-the-go. Thanks to the growing trends to bring industrial technology into the consumer-sphere, what was once technology used only by knowledgeable clinical professionals is now entering a wider commercial market.

5.1 Hospital

Within the hospital, data science strengthens the analytical abilities of clinicians for their patient's care. Clinicians often rely on clinical trials for their decision support, but these trials can be limited in their application because they are constrained in their range of demographic and patient types. For instance, they tend to focus on patient types such as those without many comorbidities (Heiat, 2002). Machine learning can reach beyond the scope of a clinical trial to analyze a more robust range of patients. Analytical technology exists that can analyze similar patients and compare their treatment outcomes through different treatment plans. This analysis can be shown to patients to help them choose their desired treatment plan alongside their physicians. Due to this, machine learning can bolster analytics by taking a very granular approach to assist in advancing precision medicine. Advances in precision medicine will increase the accuracy of care per individual since it focuses on each patient's unique genetic make-up in association with factors such as their age, sex, geography, race, and personal and family medical history. With such accuracy, there is less room for error. For example, when a diagnosis is made and there are several options of medications that can be used for treatment, a patient may trial a series of drugs until the best one is found. Precision medicine could access the patient's profile to predict which of the medications would be optimal to avoid having to experiment with more medications than necessary.

The relationship between data science and consumerism is bi-directional. The technologies that are implemented to improve consumerism can be utilized as tools to gather patient data, which can be feed into data science models for further use in developing improved models of care. Much of the technology that has come out compliments this relationship. Through the internet-of-things (IoT), devices can communicate with other devices or databases via a connection such as Wi-fi or Bluetooth. Sometimes these devices have sensors that allow them to interact with their environment and relay its data externally. Essentially, data can be received from a device, sent to a machine learning model to improve the model, and then returned to the consumer with actionable information after being analyzed. IoT can be used within the hospital setting but has picked up a lot of space in the remote consumer arena as well.

5.2 Remote Care

Technology is being developed to allow for more distance-based care where the patient does not have to come into the hospital. Some of which relies on the IoT, this technology comes in forms such as typical medical devices that are fitted for the consumer's use. This allows for patients to be monitored on a more consistent basis because the patient does not have to come into the hospital per each time they need to receive healthcare. These devices can be used remotely and are aligned with the expectations that the consumer harnesses within an on-demand economy. Traditionally, patients have only been able to receive healthcare when they are in the presence of a clinician. Now, with new technology, patients can receive some level of care in much less time.

Where patients once had to manage a gap in care in-between doctor visits, they can now have a more immediate access to a continuum of care in between their visits or following their discharge to avoid things such as avoidable ED visits. For example, through bio-sensors that are linked to phone applications, which can be access by the patients and their health providers, patients can capture and record their health metrics for their personal and clinician's review. Further, technologies have given healthcare consumers more control over their healthcare. With easily purchasable, user-friendly health devices currently on the market, patients do not have to rely as strongly on healthcare professionals to assist them in their care.

Some machine learning technology has been developed for remote care and has shown positive results within research. For its users, machine learning algorithms have been able to discern 75.8% of acute aggravations of chronic obstructive airway disease early based on sound. These detections, on average, have enabled the users to seek care five days earlier. Other algorithms have caught children's asthma decline a week ahead of them presenting symptoms, perceived seizures, and been implemented into carpets to recognize if a user has fallen (Stewart, 2018). Outside of these few examples, many companies and state actors have been paving the way to advance machine learning into the public sphere.

Dynosense has developed several biosensors that transfer results to a cloud for analysis and recording purposes. They offer devices that measure a wide array of vitals including electrocardiogram (ECG) and photoplethysmography (PPG) waveforms, blood oxygen saturation (SpO2) levels, blood pressure, heart rate, and body temperature. Once the results from these devices are uploaded to Dynosense's cloud, a health record is established. The results are then examined through machine learning methods to provide the users with real-time personalized analysis and recommendations. Clinicians can also have access to the information and interact with their patients through it (Dynosense, 2021).

The Apple Watch is a similar innovation that offers more of an on-the-go application. Where the Dynosense devices are also portable, they lack by comparison in several areas that consumers may wish to have. For example, the Apple Watch is aesthetically appealing. This is useful because the more visually pleasing the medical device is, the more likely consumers are to be engaged with them (Jarrahi, 2018). This engagement allows clinicians to collect more data to assist them in making better decisions for the patients to improve their health (Greysen, 2016). To enhance patient engagement to improve patient health outcomes, the Mayo Clinic ran a trial where they provided their patients with iPads that ran their myCare application. This application gave the patients their in-depth treatment plans, educational materials, and a daily "To Do" list. It also tracked their progress for them and their providers which promoted the transparency of their care. Of the participating patients, over 90% reported an overall satisfaction with their care and that they felt very informed about their care while in the hospital. Additionally, 98% reported that their engagement with the application equip them to better manage their health upon leaving the hospital

(Cook, 2016). Although this study was issued within the hospital, it could be executed within a remote setting.

The Apple Watch is also advantageous because of how functionally consumer-friendly it is since it can be worn as an accessory and can run in the background throughout the entirety of a day, where the Dynosense devices cannot be as readily worn and are limited in that they can only be utilized through an active use of them. Albeit some of the watch's capabilities, such as its ECG application, need to be activated per use and cannot run in the background, other heart monitoring and fall monitoring applications can operate in the background. Beneficially, the watch can constantly monitor the users heart rate and heart rhythm and inform them with notifications when any irregularities arise. Further, if a user falls, the watch can detect this and present them with a notification that they can press on their watch that, like Life Alert, immediately calls emergency services. Additionally, if the button is not pushed after approximately one-minute, emergency services will automatically be called. All the data collected from the watch can be recorded to its associated health record application. This record can be set up to provide access to emergency service and other clinical professionals via the users iPhone without the professionals needing the phones passcode. This is useful in emergency situations where health information such as a prescription and medical history is needed to provide the patient with optimal care (Apple, 2021).

The constant monitoring of a patient's heart rate through wearable devices has been shown to detect atrial fibrillation outside of the hospital setting. In one study, the Apple Watch's PPG sensors informed the user and their health provider of their arrhythmia. Once they were notified, the user was encouraged to have a telehealth consultation via their iPhone with a clinician. If their condition was urgent, they were directed to go to the ED. If it was not urgent, they were sent an ECG patch for further observation. Of those who used the patch, 34% were diagnosed with atrial fibrillation. Essentially, the watch provided extra oversight over the user's health which enabled them to receive an early diagnosis of their condition. This early diagnosis could prevent later and more serious complications such as a stroke (Perez, 2019).

5.3 Data Utilization

Data accumulated from these technologies can be put to great use in data science. Currently, the devices tend to store their data in the health records that are associated to the device and are not interoperable to the patient's other health records, such as those managed by their healthcare provider. With advances in the future to link the records together, the patient's health record could become more organized. Additionally, the data from these technologies could be amalgamated for machine learning. For instance, using data based on continuously accumulated data from the devices could allow machine learning algorithms to learn how a disease progresses. This sort of analysis is something that has not been completed on a large scale (Wong, 2020).

To fight COVID-19 Apple and Google has teamed up to develop an app that collects COVID-19 data from users and formats it for public consumption. Although this app may not analyze how a disease progresses on a clinical level, it can be useful to track how it spreads. Users that receive a positive COVID-19 diagnosis are given a six-digit code from their state's health department and they input the code into their app. Upon doing this, the app will track their location and anonymously alert other users if they were within close contact with them, as defined by being within six feet for at least 15 minutes. This app has been implemented by at least 14 states (Hamill, 2020). Apps such as this could be great for generating data that can be constructed into information. This information could advise the public of things such as where the hot spots are for and their level of exposure to other public health related conditions.

To figure out what services and products a company's consumers are looking to purchase, a company can use more traditional techniques such as surveys. Consequently, this may return scant results because it is limited to only those who respond, and the respondents may not be representative of the entire consumer base. To reach a larger response rate, many technology companies require those registering a new account with them to agree to terms that render them able collect their data. Essentially, this provides the companies an opportunity to conduct consumer research with an early acceptance of consent. With this consent, companies are free to conduct research without the need to receive further consent each time them would like to do research. Being that research within healthcare organizations is being done on a consistent basis, healthcare could learn from this early issuing of consent. This would enable healthcare organizations to *automatically* conduct research using artificial intelligence with the data they are provided. Consumer data can be collected with artificial intelligence from every consumer and automatically be transferred into already developed code for analysis. This will make it much easier for data to be used to show an organization essentially anything they would like to know about their patients.

For example, Amazon tracks their user's data such as their viewing patterns and purchase history. With this data they can make targeted item recommendations for their consumers. In fact, 35% of their sales come from these recommendations (MacKenzie, 2018). Even better, 80% of the views on Netflix comes from Netflix's recommendations (Gomez-Uribe, 2015). This targeted marketing creates a personalized online marketplace that encourages consumerism. With examples such as those, the artificial intelligence that enables this effective type of marketing really shows how influential technology can be in persuading market decisions.

Data has become the gold of businesses. The more data they have, the more information they can curate to drive their business strategies. To obtain data, companies have started new service lines that draw in consumers with attractive incentives. Essentially, consumers find the service lines appealing, so they give their business which provides their data to the business. This data is retrieved through the consumer's account information and tracking of their online behavior. For instance, online pharmacy services have been created to provide patients with further options for how they receive their prescriptions. These services improve the patient experience which attracts consumers who they can extract data from. Some of these services are being established through traditionally non-healthcare technology companies.

Amazon's newly available pharmacy service, Amazon Pharmacy, is one company that has done this. Their services attract consumers through more control and transparency. Consumers can use their online accounts to access their pharmacy information such as their prescriptions, doctors, and insurance information. The service also delivers the prescriptions, so the consumer does not have to leave the home, automatically completes refill requests, sends consumer friendly prescription directions with pictures of the medications, and offers the consumer the chance to speak with a pharmacist at any time. Additionally, PillPack is offered within their pharmacy and provides customized prescription delivery options to make it easier for their consumers to take their medications.

For example, their consumers can choose between personalized options such as whether they want their prescriptions to be delivered in a bottle or daily packages labeled with date and time directions. As for transparency, their services provide detailed pricing information such as what the copays are and what the medications are costing (Amazon, 2021). Traditionally, it can be difficult for the consumer to figure out their healthcare cost. Hence, this transparency alleviates some of that uncertainty. Overall, Amazon Pharmacy collects data from consumers across the United States where many other pharmacies tend to only have access to more localized populations. This allows Amazon to analyze a much large breadth of data to draw conclusion towards things such as how different populations and regions prefer their pharmacy experience.

6.0 Economics

The US spends nearly 18% of its annual GDP on healthcare, which comes out to $3.8 trillion, or over $11,000 per person (CMS, 2021). Further, it is estimated that 25% of total spending on healthcare is waste which composes about between $760 to $935 billion a year (Shrank, 2019). With the use of big data, healthcare could save approximately $300 billion a year by eliminating unnecessary cost such as waste (Manyika, 2011). Applying data science can be costly, especially at a larger scale with technical methods, but it cannot be ignored since it will become more of a staple within the industry as it advances through innovation. A commonly stated reason why data science has not been implemented as much as it could is because it has high starting capital cost. Expensive software and an infrastructure of hardware would need to be purchased and specialized staff may need to be hired or received additional training. Even though the initial cost may be high, the return on investment may be worth the investment. For instance, a correlation has been found that hospitals who have higher operating margins utilize dashboards from their EHRs (Gasoyan, 2020). Further, data science could bring cost savings to the overall healthcare system, which could be a major factor in reducing the cost of healthcare for the consumer.

6.1 Emergency Department

The ED has maintained itself as a pressing area where improvement could be made due to its need for quality care during crisis control situations and precedent for having high rates of utilization. From 1999 through 2009, the number of visits to EDs increased 32%, from 102.8

million visits (Raita, 2019). From 1996 through 2010, ED use accounted for 47.7% of hospital-based care and grew year after year (Carr, 2017). More than 40% of patients come to the hospital via the ED. Additionally, about 10% of all US healthcare expenses are amassed within the ED (Raita, 2019).

From the most to least critical, the CDC has addressed five patient types for the ED: immediate, emergent, urgent, semi-urgent, and non-urgent. Evaluating data from US hospitals from 2009, they found that the average wait times were 28.9, 51.2, 63.3, 58.7, and 53.5 minutes, respectively. Also, 5% of ED patients had an average wait time of more than three hours. Further, these numbers sharply differ based on ED patient volume. EDs that received 20,000 patients per year had 106.5% less of a mean wait time than EDs that received 50,000 or more (Hing, 2012). Through the lens of a patient centered mission, these figures are remarkable, especially considering that increasing a critical patient's wait time by 10 minutes rises the cost to care for them by an average of 6% (Woodworth, 2019). Thus far, along with deep learning, research into the accuracy of data science algorithms being used via machine learning has identified several algorithms to be more accurate than traditional emergency severity indexing methods: decision tree, support vector machine, random forest, RODDPSO, naïve bayes classifier, Bayesian network, lasso regression, and gradient boosted decision tree (Shafaf, 2019; Raita, 2019).

Issues such as these have inspired healthcare organizations to implement data science-based solutions. For example, the Mayo Clinic has teamed up with the artificial intelligence company Diagnostic Robotics to automate their intaking process for patients who present themselves to the ED. Using a questionnaire, patients will self-report their condition and a machine learning algorithm analyzes their responses using millions of data points from EHRs and billions of data points from other US and Israeli data sources. Being used as a tool to expedite the ED process, this analysis will determine a hospitalization risk-score and potential diagnosis (Pennic, 2020).

6.2 Adverse Drug Events

13.1% of hospital readmissions have been partially or primarily related to adverse drug events (ADE). Of those ADEs, 92.9% have been found to have been avoidable (Dalleur, 2017). MedAware has developed a machine learning algorithm to improve these numbers. Their algorithm evaluated 373,992 patient records from the Massachusetts General and Brigham and Women's Hospitals outpatient clinics and flagged 10,668 potential errors and ADEs. Researchers assessed a random sample of 300 of these flags and found that 92% of them were correct, 79.7% were clinically appropriate, and 68.2% would not have been caught by other decision support systems. Further, the researchers appraised that each flagging would save $60, which turns into $1.3 million when extended across the hospital's entire patient population.

6.3 Drug Discovery

On average, not including the time it takes to discover a drug, it takes about 10 years for a drug to pass through every phase of the clinical trials and become available for use. Depending on the research, upon being discovered, a drug has about between a 1% to 3% chance of reaching the market. Once drugs enter phase one of clinical trials, their chances are increased to 9.6% and 13.8% (Wong, 2018). Additionally, drug development costs have been increasing and now, on average, cost about $2.6 billion (Dimasi, 2016). Considering the further large amount of capital needed to market the drug, the developmental expenses act as a disincentive for pharmaceutical companies to invest in new drugs. Data science can be used primarily in the space for research and develop in areas such as drug development, and modification.

Machine learning for drug discovery is still novel and publicly available research has been limited. It has mostly been applied via business activity through partnerships between pharmaceutical and technology companies. Some of these partnerships include:

- Pfizer and IBM teamed up to use IBM's Watson technology to analyze immune-oncology data in search of new potential drugs (Pfizer, 2016)
- Also focusing on oncology, Genentech partnered with GNS Healthcare to develop drugs for precision medicine (GNS Healthcare, 2017)
- Johnson & Johnson and BenevolentAI is looking for alternative uses for currently on the market drugs (Ricci, 2016)

6.4 Physician Burnout

With newer physicians being more likely to report burnout, a little under 50% of all physician's report burnout (del Carmen, 2019). Annually, within the US, about $4.6 billion is associated to physician turnover and reduced clinical hours and has been linked to burnout. This breaks down to approximately $7,600 per employed physician (Han, 2019). To avoid adding more stressors to physicians, it is important to ensure that machine learning tools are implemented to compliment the clinical workflow. EHRs are a widespread information technology that have been criticized by physicians for interfering with the timeliness and effectiveness of their work. Machine learning could be used to limit this interference.

The 2009 Health Information Technology for Economic and Clinical Health Act (HITECH Act) incentivized healthcare providers to adopt EHRs. Before this act, EHRs were rarely used with only 9.4% of non-Federal acute care hospitals using them in 2008. As of 2015, their use has risen to 83.8% (Henry, 2016). In 2014, the Affordable Care Act mandated for healthcare practitioners to use EHRs. These two acts brought EHRs front and center to healthcare, but physicians have had mixed opinions. A common physician complaint is that the EHR requires them to put in many more hours of work per week just to do administrative tasks. Not only do many believe this, but they many also feel that the extra work does not improve the care for the patient (Meigs, 2016). With the current physician shortage, it is imperative to have the machine learning work around the physician's needs. If they require physicians to make large work life adjustments to accommodate the machine learning, this could act as a major disincentive in attracting new or retaining physicians. Machine learning should enhance its user's experience, not make their work more burdensome. As machine learning has proven in other areas of healthcare, it can have an ease of use which presents a positive outlook for reducing physician burnout.

7.0 Challenges

The peer reviewed research into the cost-effectiveness of data science is indeterminate (Wolff, 2020). Although research has shown evidence for the clinical benefits of data science, research into its return on investment needs to be further investigated. Without conclusive evidence that shows the financial benefits of data science for healthcare delivery, potential adopters may be tepid to implement it.

Additionally, the research regarding the application of data science in healthcare delivery for healthcare consumers is very limited. Most of the peer reviewed research has investigated how data science can be applied. There have been no peer reviewed research investigating the effectiveness of applications built for healthcare consumers or how these consumers feel about them (Lau, 2019). This scarcity of research presents an opportunity to further investigate specific applications to see how they exactly work on a fundamental level and benefit the consumer's health. Further, researchers should work with consumers to hear their opinions to better design products and services around what they want.

Although the growing volume of data within healthcare is beneficial because it allows for more opportunities to implement data science, there have been problems making this data functionable. For example, data from EHRs can be difficult for machine learning algorithms to decipher (Ghassemi, 2020). To decrease these sorts of problems, technology has been improving to specifically target this. MIT has developed algorithms to better collect data. Through an increase in the speed of data collection, their algorithms can train machine learning models quicker which speeds up the rate that data science technology can be implemented.

Associated to the volume of data is where it will be stored and how it will be accessed. Considering the confidentiality and sensitivity of healthcare data, this data will need to be stored and accessed securely. The rate of reported data breaches has been increasing over the past 10 years as 94% of healthcare organizations have reported being the victim of a cybersecurity attack. Cybersecurity breaches come from hacking (62%), unauthorized access (12%), theft (10%), unknown (10%), and the losing of records (6%).

Being that data flows through many different outlets, a healthcare organization must ensure that every outlet is tightly secured to avoid any breaches. This includes online and hardware security, and the execution of best practices for physical data such as paper copies of patient records. This security must also be utilized among partners who healthcare organizations choose to share their data with. For example, Quest Diagnostics and LabCorp shared data with a partner who had a data breach which compromised 19 million patient records (Pandey, 2020).

8.0 Conclusion

Data science's capabilities to automate, standardize, and more quickly process data holds a very high potential to improve the healthcare industry. Currently, there are many companies who have designed tools for data science, largely focused on machine learning, that have shown much success, but a lot of its future is speculative regarding how far these tools can be taken and to what effect they may have. These tools are applicable to both the hospital and remote settings and can bind the two together. Data science can be applied to work related to healthcare administrators and clinicians to remove the need to complete time consuming unskilled, mundane administrative tasks and assist in making better decisions. For example, data science can track and analyze key performance metrics for administrators, while also performing diagnostic and prognostic tasks for clinicians. Further, while doing this, it can save reduce waste, and compliment healthcare's move towards consumerism.

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