Overcoming Barriers to the Incorporation of Diagnostic AI in Medicine:
Lessons from Previous Innovative Medical Technologies

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

On a late January night in 1812, a mob hellbent on violence barged into George Ball's textile workshop in Nottingshire, England, laying waste to the same machinery that had taken their livelihood and caused them overwhelming grief. It was a revenge, of sorts. A revenge enacted against the inevitable tide of technological progress. This mob comprised the original "luddites". Although their name has now become a derogatory term used to describe close-minded individuals resistant to progress, the luddites were originally a group of unemployed skilled artisans who echoed some of the same sentiments held by modern-day workers who have lost their livelihoods to automation (*The National Archives Learning Curve | Power, Politics and Protest | The Luddites*, n.d.). Throughout history and even now, issues such as technological unemployment have created fears against the implementation of innovative technologies within various workspaces (Chuang & Graham, 2018). These fears lead to barriers and other forms of resistance towards innovation, ultimately hindering the proper implementation of new technologies.

Although automation has historically impacted low-skill workers the most, with the advent of AI and machine learning, high-skill workers are predicted to see similar encroachment within the next decade (Frey & Osborne, 2017). With AI being utilized in fields as diverse as banking, retail and education, one particular professional setting where its implementation could prove to be extremely disruptive is that of healthcare. If utilized as an aid to diagnosis, it has the potential of being a breakthrough technology that can revolutionize the healthcare industry as we know it. As such, this research paper aims to answer the following research questions: How might diagnostic AI reshape the landscape of medicine in the coming years? What forms of resistance and ethical dilemmas can be expected to the widescale implementation of such a technology? How might these barriers be overcome? Specifically, what insights can be gained through examining case studies of previous innovative technologies within healthcare?

Introduction to Artificial Intelligence, Machine Learning and Deep Learning

AI, at its core, is the branch of computer science that seeks to answer Alan Turing's question of "Can machines think?" It is an endeavor to replicate or simulate human intelligence within machines. In their seminal work, *Artificial Intelligence: A Modern Approach,* authors Stuart Russell and Peter Norvig divide the study of AI into four approaches: thinking humanly, thinking rationally, acting humanly, and acting rationally (Russell & Norvig, 2009). In modelling the same sort of decision making physicians deploy when diagnosing medical complications, diagnostic AI tries to simulate human intelligence by focusing solely on the "thinking", rather than the "acting".

Although machine learning and AI are used synonymously, they are not one and the same. Machine learning is but a subset of Artificial Intelligence. It is one of many approaches that can be taken to power artificially intelligent systems, with other approaches being deep learning and simpler algorithms (*What Is Artificial Intelligence? How Does AI Work? | Built In*, n.d.). Machine learning refers to a set of methods that has the ability to detect patterns in data automatically in order to predict data trends or for decision making in uncertain conditions (Murphy, 2012). It requires some training data, that is ideally representative of the whole set of data that can be provided as input to the algorithm. The efficiency of the algorithm is usually measured on a test data set after training.

Machine Learning can be split further into supervised learning, unsupervised learning and reinforcement learning. Supervised learning refers to classification or regression problems where the data must be labelled for the algorithm to make proper predictions. Unsupervised learning refers to problems such as clustering where no label is required to produce decisions on a given sample. Lastly, reinforcement learning refers to the type of learning where the machine learns by communicating with its environment through a system of rewards and punishments.

The most promising use of machine learning in present day is as an aid to diagnosis. Currently, due to the ambiguous nature of medical issues and the vast number of treatments present, different doctors with varying levels of exposure and experience can provide starkly different treatments for the same diagnosis. Additionally, in some cases where the issue itself is hard to diagnose, differential diagnosis can be both expensive and time-consuming, especially when doctors are lost as to what underlying issue may be causing symptoms. Machine learning can encompass the wisdom of multiple doctors depending on the training data and can also aid in diagnosis, especially in medical specialties that rely on image-based diagnosis (Rajkomar et al., 2019) ("Ascent of Machine Learning in Medicine," 2019).

Specifically, within the context of diagnosis, especially image-based diagnosis, deep learning plays a very influential role. Deep Learning is a subtype of machine learning capable of delivering a higher level of performance without the need of a human to identify and compute the discriminatory features for it. It resembles the multilayered human cognition system and the algorithms for deep learning are even referred to as neural networks. The multiple-layered networks of these algorithms are used to assess complex patterns within the raw imaging input data which is why these algorithms are well suited for medical imaging analysis (Giger, 2018). They provide a significant advantage over classic machine learning methods as the algorithms are much more scalable. In simpler terms, this means that the performance for this class of algorithms keeps increasing as you feed it more data whereas with previous machine learning methods performance ended up plateauing after a certain data threshold was reached (Brownlee, 2019).

Actor Network Theory as an Analytical Framework

In order to analyze how the healthcare system is impacted by the incorporation of Artificial Intelligence both on a macro and micro level, it is necessary to chart who all the different actors are and how they impact each other. The actor network theory (ANT), thus provides a framework that analyzes the interplay between the different actors, be they human or non-human, as is the case with the artifact of Machine learning (Cressman, 2009). This framework allows for investigation into how networks come into being, what associations exist, how actors are enrolled into a network, how power is established and how networks gain temporary stability (Cresswell et al., 2010). Although ANT offers a broad analysis of interactions between both human and non-human elements, there are some inherent limitations associated with using this framework. Even though there may be differences in status between all the actors, equal importance is ascribed to all actors within the network, which can lead to incorrect attributions of an actor’s true impact over another actor within the network. Additionally, actors in the network are defined by the author themselves, which can leave a lot of room for subjectivity in the analysis. If the author incorrectly chooses a very narrow list of actors, the analysis may completely miss or incorrectly attribute the impact of an invisible actor over the entire network.

Application of Actor Network Theory to AI in medicine

To apply the Actor Network Theory framework when exploring the impact and forms of resistance that may emerge in response to the implementation of Artificial Intelligence in diagnostic medicine, it is imperative to first define who all the actors are and where they fit in context of this new technology. Caregivers and patients seem to be the two most obvious actors in this network as the institution of a hospital is founded on the relationship between these two actors. Here, “caregivers” is used as a general term encompassing physicians, nurses, physician assistants, etc. Another very influential actor within the sphere of medical care includes hospital administrators, representing the interests of increasing profits within the business of medical care. As mentioned earlier, the introduction of diagnostic AI as an actor within this network of medical care has the effect of introducing instability which occurs through changing dynamics between existing actors as well as through the introduction of new actors. Some of these new actors include companies and startups focusing on the development of diagnostic AI, researchers looking into how such technologies can be improved to produce optimal and accurate results, and regulatory bodies such as the FDA that are responsible for ensuring that the harms involved with the application of AI in medicine are reduced to as little as possible.

Barriers to Implementation of AI Diagnostic Softwares

There have been several concerns raised as to the adoption of AI within medicine, many of them centered around the attitudes of medical care professionals. These include beliefs that the technology could affect professional autonomy while diagnosing or treating patients, that it may be used as a means of control by hospital administrators and that it may interfere in the relationships between medical professionals and patients (Safi et al., 2018). Another issue comes from the fact that AI applications can cause significant legal and ethical problems. Currently medical care is set up such that healthcare is delivered to care recipients through an accredited medical professional who has trained for several years and has the best interests of their patients in mind. With the introduction of AI that can make effective diagnoses and prescribe proper healthcare regimens independently of physicians, this flow of information is circumvented and a loss of ethical and legal responsibility emerges (Ho et al., 2019). Additionally, other issues specific to AI are also likely to surface within medicine. These include bias inherent within modern-day medicine as the training data may contain these biases and lead to propagation of such preferences when the AI is used in the diagnosis of real patients. Additional institutional barriers include the fact that large scale implementation of diagnostic AI softwares will require necessary upgrades in regards to infrastructure such as with hardware and improved cyber security measures (Ho et al., 2019). The majority of the burden for such an endeavor will fall on IT professionals and may even lead to the formation of new positions specific to these technologies such as medical data scientists, as discussed later in the paper.

These are just a few of the issues that offer brief insight into the complexity of introducing AI in medicine, highlighting the importance of tackling and overcoming these barriers head on if we hope to see successful implementation of such technologies in the coming years. Looking back at previous innovative technologies and analyzing how similar barriers were overcome in the past might offer insight into what measures must be taken to reduce forms of resistance and to overcome certain barriers. This analysis may also allow for a better understanding of what other barriers may emerge as diagnostic AI is put into use. In the sections below, the stories of two breakthrough technologies are discussed: laparoscopic surgery procedures and Electronic Health records. Both faced forms of resistance that were ultimately overcome to some degree and can provide insights regarding strategies that may be useful when confronting the application of AI in medicine.

Case Study 1: Laparoscopic Surgery procedures

Although laparoscopic surgery has transformed general surgery only in the past three decades, diagnostic laparoscopy has been around since the nineteenth century. Utilized initially to view the insides of the abdomen and assist in the diagnosis of various diseased states, the use of laparoscopic tools and procedures eventually became subjugated solely to the fields of gynecology and internal medicine. This occurred as the gap between general surgery and gynecology became increasingly wide with surgeons believing that gynecologists had "operation envy" and that "real" surgeries were exclusively the domain of general surgery, not gynecology (Litynski, 1998b). Gynecologists were seen as having inferiority complexes and surgeries such as appendectomies were supposed to be unattainable for someone with the profession of a gynecologist. Kurt Semm, a German gynecologist was therefore seen as an over-ambitious gynecologist, trying to bolster his "operation ego" when he pioneered the first laparoscopic appendectomy, giving rise to the field of operative laparoscopy.

Semm's achievement was monumental as he had created the world's first laparoscopic surgery procedure, which offered various advantages to the patients, beginning the trend towards minimally invasive procedures within surgery. The advantages include little postoperative pain, shorter period of immobilization, shorter postoperative hospitalization, and a rapid return to the workplace, all owing to the fact that abdominal muscles aren't cut which would have been the norm with the established procedure of laparotomy (Litynski, 1998a). As might be expected, Semm's innovative procedure clashed with the established practices and therefore physicians of the time weren't eager to accept these new practices. They saw no reason to change well-established practices for a complex procedure. Some surgeons believed he was "going too far" by making a surgical tool out of a diagnostic one. Many surgeons even described Semm's procedure as being superfluous. In a March 1983 article in the Medical Tribune, a journalist can be seen downplaying the adverse effects of laparotomy stating *"Postoperative adhesions can lead to complications, but they in no way occur with such frequency that one must switch to* *endoscopic operations".* He argues that if the surgical procedure was made less dangerous and easier on the patient, it may lead to unnecessary appendectomies, going onto question whether the procedure is worth it by asking "*Do the advantages of endoscopic operations—avoidance of laparotomy, diminishing the pain of the incision, early mobilization, and avoidance of post-operative adhesions—outweigh the disadvantages—greater expenditure on technology and more complicated methods of operating?"* (Litynski, 1998b).

Erich Mühe, another German doctor, inspired by Semm's innovative techniques followed in his footsteps, pioneering the first Laparoscopic cholecystectomy, a surgical procedure to remove one's gall bladder. He faced similar, if not even worse backlash and resistance from the old guard especially when he presented his findings to the German Surgical Society. The audience was skeptical of his claims, believing that operating through a small incision was dangerous. In addition, Mühe had to deal with derogatory remarks such as "Mickey Mouse Surgery" and "small brain—small incison". His findings were completely ignored, to the point where other surgeons were later given credit for performing the first laparoscopic cholecystectomy. This claim, however, was revised in 1998, 12 years after he pioneered the procedure, when Mühe was recognized by the Society of American Gastrointestinal Endoscopic Surgeons (SAGES) (Reynolds, 2001).

Both Mühe and Semm faced similar resistance from the old guard of general surgery which can partially be attributed to their training. Their unfamiliarity with laparoscopic techniques left them vulnerable to a culture shock, and therefore they were unprepared for a complete reworking of surgical concepts(Litynski, 1998b). Additionally, the perspective that large problems required large incisions deeply dominated surgical thinking in the 80s, making it hard to appreciate "key-hole" techniques in surgery(Litynski, 1998a). Therefore, naturally, what was instituted to overcome such a dominant perspective was the incorporation of the new techniques into contemporary medical education. Early pioneers in these techniques such as Saye, McKernan, Reddick and Olsen set up centers and courses to teach laparoscopic techniques to classically trained surgeons. The early teachers and trainees felt a sense of collegiality, believing themselves to be a part of a revolution in surgical thought. They, therefore, were very open amongst each other in sharing new ideas and strategies in surgery, creating a community dedicated to the promotion of novel ideas and innovations in laparoscopy (Kavic, 1998).

The media also played a role in popularizing laparoscopic procedures. During the years when academic centers and society were rejecting the laparoscopic approach, these procedures continued being performed within private practice. As word spread, an increasing number of physicians became interested and began practicing laparoscopic procedures. The media also gradually caught on, terming these procedures “Band-aid surgery” (Kavic, 1998). As patients learned about this new technique from the media, demand became at least partially patient-driven, To keep up with patient demands, surgeons had to adapt to the new ways, ultimately leading to widespread acceptance of laparoscopic techniques in surgery

Case Study 2: Electronic Health Records

The electronic health record (EHR) is a clinical information system, introduced in the mid-1960s by Lockheed. The major goal for the technology was to serve as a repository for a clinician’s observations and analysis of a patient (*The History Of Electronic Health Records | Elation Health EHR*, 2017). This technology held great promise in improving the workflow of health professionals as well as making information more accessible to patients. With all information being present in one place, it would be easier for health professionals to stay up to date with their patients histories, previous diagnoses, current prescriptions, etc. Additionally, a system would exist such that clinicians could be reminded to perform certain actions such as ordering a routine mammogram or checking the serum potassium levels of a patient on diuretic medication (Hersh, 1995). Additionally, it would provide benefits to the patient as records could be easily accessed by patients whenever they desire. Records would also be preserved better as they wouldn't be lost as easily as paper records. Clinical researchers would also benefit as they could have easier access to patient information to increase understanding of diseases and their treatments (Hersh, 1995).

Despite all these promises, the uptake of EHRs by hospitals and their incorporation into the contemporary medical landscape took decades. This was due to several barriers in the implementation of EHRs which when traced can also explain current problems with EHRs. In a study conducted in 2004, when EHR use was starting to pick up, the major barriers identified were high upfront financial costs, slow and uncertain financial payoffs, and high initial physician time costs (Miller & Sim, 2004). Average implementation of an EHR systems ranges from $14,000 to $63,000 with a median cost of $45,000. In addition, annual maintenance fees are around $7,000, making EHRs a costly endeavor (Columbus, 2006). High physician time costs also made EHRs unattractive as physicians were spending more time per patient after the institution of EHRs, leading to longer workdays and less patients seen. There were several underlying causes to the higher time costs. A huge issue was the fact that even the most highly regarded EHR softwares were challenging to use. Problems with usability would require physicians to spend more time learning how to use EHRs effectively. Physician attitudes also played a role as physicians who had a negative attitude towards new technology would be easily discouraged by usability problems, in turn not utilizing EHRs to their full capacity. The technology proved to be even more annoying for medical administrators who had to patch together and deploy technical support from the various software, hardware, networking, and service vendors when technical glitches occurred. This is in addition to the time they had to spend in the early stages arranging for EMR installation, receiving and assisting with EMR training, and encouraging EMR use among their colleagues and staff. Inadequate electronic data exchange between EHRs and other clinical data systems (labs, referral systems, etc.) would also slow down workflow, requiring users to spend time manually entering data from external systems (Miller & Sim, 2004). In addition to the lack of interoperability, other software issues would emerge including billing errors, software systems becoming obsolete, software vendors going out of business, programming errors and automated process issues (Ajami & Arab-Chadegani, 2013).

How were these issues overcome? And how did EHR adoption rates go from 20% in 2011 to 80% in 2015 and 95% in 2021 (*Does Hospital EHR Adoption Actually Improve Data Sharing?*, n.d.)? The major push in implementation can be attributed to efforts by the government to incentivize the adoption of EHRs. The government's big push began in 2009 with the passing of the Health Information Technology for Economic and Clinical Health Act, more commonly known as the HITECH act, which provided more than $35 billion in incentives to promote the adoption and use of EHRs across the nation(Reisman, 2017). The act was split up into three stages with new requirements introduced at each stage, and financial incentives increasing with each year of the program. There were also fines imposed for institutions that didn't meet requirements: a reduction of Medicare and Medicaid reimbursements ("What Is the HITECH Act," n.d.). There were additional efforts by the government to fix issues related with EHRs. One example is the Affordable Care Act which had parts aimed at fixing interoperability issues, mandating improvements in the ways lab test results were exchanged and transmitted to EHRs (Hinrichs & Zarcone, 2013).

Discussion

The two case studies were chosen as they offer insight into two vastly different innovations in medicine that each relate to aspects of diagnostic AI. Laparoscopic procedures in surgery were a deeply medical innovation and they give insight into the barriers that surface towards innovations that can impact the treatment and care provided to patients. Additionally, during the laparoscopy revolution in the 90s, the procedure was seen as a mindset for how to approach surgical problems, similar to how AI is a framework that can be applied to multiple fields within medicine (Kavic, 1998). Electronic Health records, on the other hand, don’t have much to do with the science of medicine, but surveying the barriers to its implementation can provide insight into the particular issues that accompany digital technologies.

Similar to the roadblocks faced by Semm and Mühe, diagnostic AI is bound to rouse opposition from medical providers who aren’t eager to accept change within the field. Many may even view it as superfluous or a waste of money which is why it will be of paramount importance to convince the old guard regarding the advantages associated with the use of diagnostic AI technologies. Safi et al. identify in their review of resistance to digital technologies in medicine that “resistance must be identified and reduced by greater awareness of the technologies and convincing potential users of advantages associated with the use of these technologies” (Safi et al., 2018). This would also require proof of sufficient proficiency on the part of research groups and companies involved with the production and development of diagnostic AI.

To ensure proper incorporation of diagnostic AI within the field, similar to the route taken by early pioneers in laparoscopic surgeries, courses can be set up to educate physicians on how to seamlessly incorporate diagnostic AI applications as part of their workflow. A basic understanding of Artificial Intelligence and Machine Learning as part of these courses may also be beneficial. With the surge in research of Medical image analysis softwares that apply AI, there have been calls by medical bodies such as the Canadian Association of Radiologists, that believe radiologists using Computer associated diagnosis must be able to open the black box of AI and understand how at times, certain decisions outputted by the technology have no technical or logical reasoning behind them (Tang et al., 2018). Therefore, understanding the technicalities behind AI may assist with the proper use of these technologies as they are incorporated into contemporary medicine.

Using the case of EHRs as an example, similar issues with physician attitude may be possible where some physicians may not buy into the idea of diagnostic AI, leading to a clash with existing practices. This may also lead to improper use of the technology and slower adoption as was the case with EHRs when they were introduced. The initial costs would most likely be very high due to the complexity of the technology, which is where government incentives similar to EHRs would be very beneficial. Government assistance can also act as both positive and negative reinforcement by implementing punishments if diagnostic AI is not implemented given a certain period of time. Of course, this would all depend on whether researchers can produce enough scientific evidence to convince them that such an endeavor would be worthwhile considering the benefits offered by the technology. Additionally implementing diagnostic AI would require investment in IT personnel that are trained in data science applications which itself may not be a significant issue considering most hospitals already have IT personnel to aid with issues with EHRs and other technologies. This would create a barrier for smaller practices, where the government may need to step in to incentivize the transition to implementing diagnostic AI.

Conclusion

The marriage of AI and medicine is one that holds great promise for the future of healthcare as well as for all the actors involved. However, the proper implementation of Diagnostic AI depends on identifying barriers and forms of resistance, and then reducing and overcoming these barriers. Previous innovative technologies such as laparoscopic surgery procedures and Electronic Health Records provide historical case studies which can be studied to identify both potential forms of resistance and strategies to overcome these barriers. Through learning from the past, those involved with the implementation of diagnostic AI can be better prepared and the transition into integrating this technology into normal workflow can be made much smoother.

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