# Medical Analytics in Health Care Networks

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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.

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**Medical Analytics in Health Care Networks**

According to one physician: “My hope is that it will allow a breadth of perspective not yet captured by either the anecdotal experience of the individual clinician or individual research studies, and that it will increase analytical speed and power to assess interventions or treatment choices” (Char, qtd. in Ward, 2019). Data analytics’ widespread use in medical research, clinical care, and insurance provision has led to numerous well documented, uncontested benefits. Publications provide ample evidence for this in analysis of bioinformatics and medical AI in clinical and research settings. With large-cohort clinical data, healthcare networks have applied data analytics to the longstanding claims-based analytical systems. Bioinformatics can disclose disease propagation at the molecular level (Bellazzi et al., 2012). Clinicians apply the results of analytics to improve therapies (Raghupathi & Raghupathi, 2014). With data analytics, medical institutions can better manage and interpret patient data. It can also improve communication between medical centers and their patients, with consequent efficiency benefits (Y. Wang et al., 2019). Insurers and their policyholders can benefit too. Policies can be individualized, reducing costs; coverage may thereby be extended to more people (Ho et al., 2020). Public health informatics can help patients and others learn about healthcare and treatments (Sweeney et al., 2017). Yet data analytics introduces new hazards, and its proper place in medicine is contested.

“The first fear is that AI and machine learning may worsen the economic and racial disparities already inherent in U.S. health care” (Char, qtd. in Ward, 2019). Doctor Char’s two statements convey a dual view of medical analytics in medical research and practice. Physicians, patients, researchers, and medical institutions have growing concerns about implementation of software into medical networks. Donor privacy is essential for the ethical handling of patient data in medical analytics. Agencies central to healthcare networks including the Center for

Disease Control (CDC), American Medical Association (AMA), and patient advocacy groups have systems to ensure proper handling of data (AMA, n.d.; CDC, 2019; WEGO Health, 2018). As data collection becomes more rigorous, applicability of privacy measures has been brought under scrutiny and potential solutions have been considered (Basso et al., 2016). Bias can also pose challenges to medical analytics. “AI systems are only as good as the data we give them” (Krasniansky, 2019). Racial and gender biases in research data can lead to misdiagnosis in downstream clinical applications (Larrazabal et al., 2020). Data quality, viability, and considerations to patient safety can be viewed as negative caveats to analytics in healthcare (Mantas et al., 2017). In the U.S., medical analytics and the data collection it depends on have been distinguished as a means of rapid improvement in healthcare, but certain interest groups warn that it can exacerbate current ethical issues and must therefore be regulated.

**Literature Review**

Data analytics and associated big data are utilized in many fields. Implementation in government, social media, business, and health care have been researched heavily. Perspectives of involved members within these fields will establish how they have reacted to data analytics, competed for and developed patient datasets, and negated or promoted ethical risks in the process. Actor network theory (ANT) is an established framework that can be useful for analyzing intangibles within networks like healthcare (Cresswell et al., 2010). Views of involved individuals will be analyzed through ANT and other conceptual approaches to give insight on the questions and claims presented.

Big data, critical for training analytics tools, has garnered the focus of researchers. Zwitter (2014) details the ethics shifts due to big data by investigating the role of ‘big data collectors, utilizers, and producers’ from an ANT framework. Shifts in power between these actors can create new ethical considerations: digital manipulation of the public, crime probability and guilt, and global algorithms versus regional expertise. Iyamu (2018) created a multilevel framework based on ANT to enhance the quality of big data analysis from multiple views. Researchers have also reviewed and proposed solutions to privacy issues inherent to big data. Wu and Guo (2013) propose a model to preserve data privacy by displaying precisely how user data is being utilized within applications. Similarly, Li et. al. (2013) presents a cloud software architecture that excludes a virtual control machine to aid in user privacy.

Data analysis in tangential fields is relevant for analysis of similar tools in healthcare. Hartmann et. al. (2016) develops a baseline framework for analyzing how start-up companies can develop data-driven business models. Another researcher conceptualizes privacy issues of big data with respect to market researchers who seek financial opportunities from public data (Nunan & Di Domenico, 2013). One group of researchers presents information on social media big data privacy invasions, and expands their case study to various African country data privacy legislatures (Shozi & Mtsweni, 2017). Singh et. al. (2018) couples analyses centered in business and social media to establish a means of utilizing tweets to enhance supply chains. Data analysis in government is also applicable to the study of medical analytics in healthcare as explained by Archenaa and Anita (2015) who weigh benefits in both.

Patient privacy and strategies to maintain it have been a focus for researchers in clinical fields. Authors have expressed concern over the lack of technical solutions in electronic health records (EHR) and the role nursing can play in the privacy of EHR (Milton, 2017; Ray & Wimalasiri, 2006). Ethics are also discussed as it pertains to data analytics biomedical research in the hopes of lessening over-optimism (Mittelstadt & Floridi, 2016). Qualitative reviews on medical analytic applications in healthcare, and various frameworks for improving their use have also been researched (Chauhan et al., 2021; Iyamu, 2020; Mehta & Pandit, 2018).

**Analytics Shaping Medical Research**

"Biomedical research saves, improves, and enriches human lives" (Goodman, 2016, p. 121). Researchers apply data analytics as bioinformatics and medical AI to sequence DNA, RNA, and proteins, and to derive functional pathways by quantifying gene expressions across donor data (Gauthier et al., 2019). Informatics is widely used in clinical genomics, genomic medicine, and pharmacogenomics (Bellazzi et al., 2012). Researchers apply data analytics in the discovery of molecular targets in disease, the identification of genetic pathways and endocrine function, and analysis of human evolution and disease through transposable element and miRNA data (Ayo et al., 2020; Dasari et al., 2020; Seldin et al., 2018). Bioinformatics has also been widely applied in the study and diagnosis of Covid-19 during the ongoing pandemic (Feng et al., 2020; Kim et al., 2020). Biomedical researchers have become reliant on bioinformatics, yet some issues with analytics remain apparent in the field.

Data analytics has had some detrimental effects in the communication, accessibility, and reproducibility of medical research. Insufficient standardization across biomedical fields has complicated large-cohort biological data storage and the use of software programs developed by researchers (Stein, 2002). Kouskoumvekaki et al. (2014) recommend standardization of data presentation to promote data analytics in healthcare research. Riegman et. al. (2019) also supports this notion by identifying methods contributing to irreproducibility and metadata methods to decrease it in biomedical research. Kalet (2014) has proposed that biomedical data be organized and represented efficiently to researchers through 3 dimensions: structure, encoding, and context. Researchers will know how data is stored, what computer programs can utilize the information, and how data is organized into logical units.

One researcher states, “The main negative aspect of this new data-driven medicine is its impact on privacy” (Berrang et al., 2018). “Inappropriate use of these data might lead to leakage of sensitive information, which can put patient privacy at risk” (S. Wang et al., 2020). Biomedical researchers have shifted focus to maintaining patient data privacy in response to increasing biological data collection and decreasing costs for molecular profiling. The Health Information Technology for Economic and Clinical Health Act (HITECH) mandated the use of Electronic Health Records (EHR) in the U.S to improve clinical care (S. Wang et al., 2017). EHRs have phased out paper ones, and while little contention to this shift exists, Goodman (2016, p. 6) claims there is an obligation to improve them. EHRs need to facilitate reliable decision support in research of patient health, be interoperable, and contain data central to patients.

S. Wang et al. (2017) discusses the ethics of EHRs and genomic data in biological research. Genomic studies will usually remove any potentially identifying information from their produced data sets. De-identified data is exempt from federal privacy protections most notably the Health Insurance Portability and Accountability Act (HIPAA). Various linking methods can be used to re-identify subjects within data sets. "If there’s enough data out there, someone can mash it up and use it to identify anybody” (Dr. Kohane, qtd. in Marpuri, 2013). “Very limited legally protected interests in personally sensitive, imperfectly anonymous data makes cryptographically secure protocols for genomic data absolutely critical” (S. Wang et al., 2017). Potential privacy breaches have led to researchers formulating frameworks for analyzing privacy risks of data sets (Berrang et al., 2018). Mohammed Yakubu & Chen (2020) along with other researchers have also analyzed means of limiting de-identification privacy breaches.

**Data Analytics in Clinical Practice**

In healthcare, including patient documentation, data analytics affects clinicians and hospitals. Analytics may offer clinicians new drug targeting methods, large populous DNA and protein sequencing for individualized genomic analysis, and screening methods for disease susceptibility (Chang, 2005). Analysis of genetic data and DNA sequencing may permit an individual's genotype to be used as a supplement to phenotype (Reches et al., 2019). Over time, phenotype-genotype correlations can be developed to support health practitioners' diagnoses and treatments (Bellazzi et al., 2012). Screening for biomarkers in susceptible patients can help doctors diagnose tumor formation earlier. Medical informatics can also help them identify effective targeting proteins or molecules in tumors (D. Wu et al., 2012). While informatics has become prominent in clinical settings, individuals have ethical concerns about its implementation.

Concern has mounted on the role of analytics tools like AI in clinical settings as they guide physician's decisions. "AI systems might take on an authority they don't deserve. There is a likely scenario where AI systems move into a role of controlling clinicians' decisions and workflow, as the electronic medical records prompts and warnings are already starting to do" (Dr. Char, qtd. in Ward, 2019). Many professionals have taken a stand, including the AMA, ensuring that medical AI will not replace the human component in patient care. "In health care, machines are not acting alone but rather in concert and in careful guidance with humans, i.e., us physicians" (Dr. Ehrenfeld, qtd. in Robeznieks, 2020). The chair of AMA continues, "There is and will continue to be a human component to medicine, which cannot be replaced. AI is best optimized when it is designed to leverage human intelligence.” Dr. Talby, CTO at Pacific AI, supports this, “There’s not going to be an AI that solves health care” (Talby, 2019). Medical AI, however, have gradually been performing the 3 tasks typically performed by doctors: diagnosis, treatment, and prognosis. “I said, ‘Well, I think it’s going to change what we do, but the good news is, at least you’re not a pathologist,’” responded one physician when discussing the prospects of AI replacement (Dr. Fishman, qtd. in Budd, 2019). Professionals maintain a positive outlook on AI-doctor relationships.

Quality of medical analytics results is another concern for medical practitioners. One professor voices his concerns of medical AI by stating that medical educations aren’t preparing physicians to practice medicine in an ‘AI-augmented environment’ (Ward, 2019). “Everyone agrees that algorithms are going to be a big part of medicine in the future, but we aren’t developing the human-capital pipeline against that goal. We don’t see it reflected in our pre-med requirements, or medical-school curricula” (Dr. Obermeyer, qtd. in Ward, 2019). Similar concerns were mentioned at the AMA State Advocacy Summit. One panelist warned to avoid “garbage-in, garbage-out” scenarios where AI are relying on data unrepresented by those being treated. Another panelist spoke, warning of “glamour AI,” new technology that doesn’t improve health outcomes (Sonoo Thadaney Israni and Dr. Abramoff, qtd. in Robeznieks, 2020). Transparency presents another potential issue to clinicians utilizing medical analytics. “Medicine uses a lot of things that we don’t understand and can’t explain. So, the last thing we’d want to do is hold algorithms to that standard. We want them to discover and help us learn about things we don’t understand. In fact, that’s most of the upside” (Dr. Obermeyer, qtd. in Ward, 2019). Professionals shared similar sentiment on AI transparency.

Ethical concerns have arisen from perpetuated bias in medical analytics in healthcare. Racial and gender bias in results of bioinformatics algorithms has become a focus in recent literature (Larrazabal et al., 2020; Obermeyer et al., 2019). "AI algorithms should mirror the community" (Dr. Kaushal, qtd. in Lynch, 2020). Director of Harvard Global Health Institute states, "We already know that the health care system disproportionately mismanages and mistreats black patients and other people of color" (Ashish Jha, qtd. in Gawronski, 2019). Racial bias in the data used to train medical algorithms can result in more 'pervasive' and 'systematic' bias (Gawronski, 2019). A physician supports this statement by saying, "When algorithms learn from us—when they learn to discriminate, to be biased—in a way, it's not the algorithm's fault. It's our own fault" (Dr. Obermeyer, qtd. in Ward, 2019). Noting that medicine has encountered these biases in the past, Dr. Kaushal (Lynch, 2020) states, "As AI is set to enter clinical medicine, we shouldn't have to wait 30, 40 years to make all the same mistakes and fix them again. We should see where this is headed and address it upfront."

**Analytics Transforming Insurance**

Data analytics, namely AI, has begun to reshape health insurance. One researcher states, "Not long ago, insurance fraud detection was not considered cost-effective because the cost and duration of the investigations were too high" (Bologa et al., 2013). The researchers conclude that big data analysis can detect abnormal claims and be used to identify new patterns of fraud. Kirlidog and Asuk (2012) make a similar claim; "Data mining tools and techniques can be used to detect fraud in large sets of insurance claim data." Srinivasan and Arunasalem (2013) research findings demonstrate that health insurance firms can recover cost overruns by utilizing data analytics tools. Researchers in Ho et. al. (2020) express ethical concerns of AI guided fraud detection. "An ethically sound and enabling environment needs to be established and sustained to support, and perhaps even steer, such technological development and implementation in health insurance." Researchers in Hehner et. al. (2017) argue that audit algorithms will reliably detect solely incorrect claims.

Health insurance companies have implemented these tools in response to the potential cost benefits. A healthcare data professional stated, "More and more, you're seeing investment in AI to intervene on behalf of customers to change behavior in ways that actually result in better healthcare outcomes" (Christer Johnson, qtd. in Forbes, 2019). Companies offering software platforms have been contracted by health insurance firms to decrease costs and increase collective health in addition to detecting fraud. One author states, "In anticipation of these market fluctuations, we can expect increased adoption of AI solutions in the health insurance industry among companies seeking to cut costs, scale up operations and improve client outcomes" (Sennaar, 2019). Other industry professionals share this positive outlook for AI in insurance. "Natural language processing, bot technology, machine learning—these processes are not just playing a key role in creating efficiencies for companies. They're creating a better health experience for members" (Torben Nielson, qtd. in Forbes, 2019).

**Patients and Analytics**

Data analytics in medical care begins with patient or donor information, and patients are typically the final recipients of these tools' outputs. A dichotomy of views has arisen from the concerns of patient privacy and the potential downstream health benefits. One physician on AI in healthcare stated, "The value is we are now reaching more people and providing better care" (Dr. Schneider, qtd. in Wharton et al., 2018). Steger et al. (2020) discusses how medical algorithm's predictive ability and clinical decision support for deadly conditions such as sepsis can save lives. Another medical expert has stated, "We're at a point of being able to predict the likelihood of a cardiac arrest in 70 percent of occasions, five minutes before the event occurs" (Peter Laussen, qtd in Salzman, 2019). While the health benefits to medical AI are apparent, concerns about their use are being addressed by medical professionals.

Trust in medical AI and the improvement of clinician-patient relationships currently limit the realization of better patient outcomes. Abraham Verghese (2011) describes a case where a CT scan, to rule out blood clots in the lung, displayed that the patient had breast tumors. Verghese states, “I got to see the CT scan: the tumor masses in each breast were likely visible to the naked eye and certainly to the hand. Yet they had never been noted.” Nagy and Sisk (2020) acknowledge the need to preserve relationships between patient and doctor. They conclude their clinical AI analysis with, “Clinicians, technology developers, administrators, and patient advocates should take steps to maintain the centrality of the healing relationship in medical care as AI technologies are developed and further integrated into the health care system.” One professor notes, “Enhancing the perceived personalization of care delivered by medical AI, and enlisting physicians to verify and endorse the recommendations of AI providers will be key to building trust and receptivity among consumers” (Andrea Bonezzi, qtd. in Ritter, 2019). Schiff and Borenstein (2019) pose that transparency to patients about the role of AI’s risk and benefits is critical to addressing patient uncertainty. Questions about the trustworthiness of medical AI in patient care have arisen in recent works (Hatherley, 2020; McDougall, 2019). Ferrario et al. (2020) and Nucci (2019) provide alternative perspectives that trust can be built between AI and patients. There is optimism for AI and patient interactions. “We’ve done a ton of research into our member experience, and we’ve found that more and more people are very comfortable engaging with technology solutions versus talking to a person” (Torben Nielson, qtd. in Forbes, 2019).

Public health database production has grown from private sector firms and government entities. HIPAA privacy does not govern big data produced by non-medical entities and their associates (Cohen et al., 2018, p. 89-90). Recently, HIPAA privacy rulings have been relaxed in response to COVID, often waiving penalties for rule breaches (Andrea Kulkarni, 2021). Fears for patient privacy in data not protected by HIPAA has led to patient advocacy groups and individuals pressing for enhancement of HIPAA. Cohen and Mello (2018) state, “To ensure adequate protection of the full ecosystem of health-related information, one solution would be to expand HIPAA’s scope.” AMA, HIPAA Compliancy Group, American Health Information Management Association (AHIMA), and the American Association of Family Physicians (AAFP) continually monitor HIPAA and publicly support the extension of privacy coverage (AAFP, n.d.; HIPPA Journal, 2020; AHIMA, n.d.; Compliancy Group, 2019). The AI Health Coalition has been established to educate and guide the ethical use of AI in medical care (AI Healthcare Coalition, n.d.). The 2013 decision by the National Institute of Health (NIH) to limit access to Henrietta Lack’s HeLa immortalized cell line set a precedent for data privacy protection globally (Begley, 2013).

**Conclusion**

Benefits of medical analytics become more apparent as work continues in related fields. Ethical concerns remain to be fully addressed on privacy and bias in research and clinical practice. Advocacy groups continue to press for improvements in federal regulations to protect individual privacy. Researchers develop frameworks for identifying, quantifying, and addressing bias in medical data. Extension of coverage for HIPAA to include currently non-covered entities may be an effective means of improving privacy for donor information. Exposing professionals to medical analytics tools early on can prepare them for clinical practice. Implementing policy, from medical institutions or federally, on clinical research can negate bias that pervades current medical databases. Medical analytics utilization is on the rise, and ethical conduct by researchers, doctors, and insurers is key for continued benefit to actors in medical networks.

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