Deep Science Publishing
https://doi.org/10.70593/978-93-49910-67-6_8

Chapter 8: The intersection of data, artificial intelligence, and healthcare: Creating predictive and personalized care models

8.1. Introduction

The proposal of the Learning Health System (LHS); real-time generation and translation of evidence into practice through seamless integration of data and analytics to support improvement of health across individuals and populations; has the promise to address many of the most pressing problems in US healthcare delivery: Access; Affordability; Quality; Equity; and Impact. Fortunately, the previous decades have seen significant advancements in technologies and methods that make the deployment of LHS in multiple settings and clinical domains at consumer-and-organization scale possible. Specifically, the rise of the Internet and popularity of smart devices have created an infrastructure that enables real-time, triggered, and proactive data collection about a patient's temporal health status outside of the clinical setting. These digital footprints, when combined with near-continuous passive health state data from devices and wearables, form a data reservoir for predictive analytics and support AI-enhanced solutions. Such predictive solutions can take the form of Risk Prediction Models or Clinical Decision Support Systems that automate aspects of clinical decision making (Ahmed et al., 2018; Kumar & Mallick, 2018; Ghosh & Das, 2019).

In this opening essay, we highlight several cross-cutting themes that will garner more attention in our planned series of essays and seminars. The first theme is how consumer-and-organization scalable predictive analytics; engines configured using LH-based Risk Prediction Models or population-and-time-and-person segment-configured Clinical Decision Support Systems; can be developed and deployed to reduce the challenges of scale, including the volume of high risk patients and high uncertainty involved in attributable care management. Also including the clinical decision-making burden throughout the care continuum associated with identification of the “right” patients that would benefit from cardiometabolic or other specialty care interventions. Finally, the mismatch between clinical, social, and behavioral resources available and the number of patients that require these resources.A clear understanding of these data sources and types is crucial for being able to leverage the right data-driven technologies to develop the right solutions from an accuracy and precision perspective. This understanding is also useful to improve the algorithms and tools for a data-driven ecosystem by providing a roadmap that considers the nuances of the healthcare data-driven approach. The healthcare ecosystem structure, initially dictated by the payer-provider-treatment dynamic, is changing with the rise of digital, consumer-driven, technology-savvy patients, coupled with an explosion of data from health systems that integrate with this ecosystem (Taleb et al., 2017; Shuja et al., 2019).

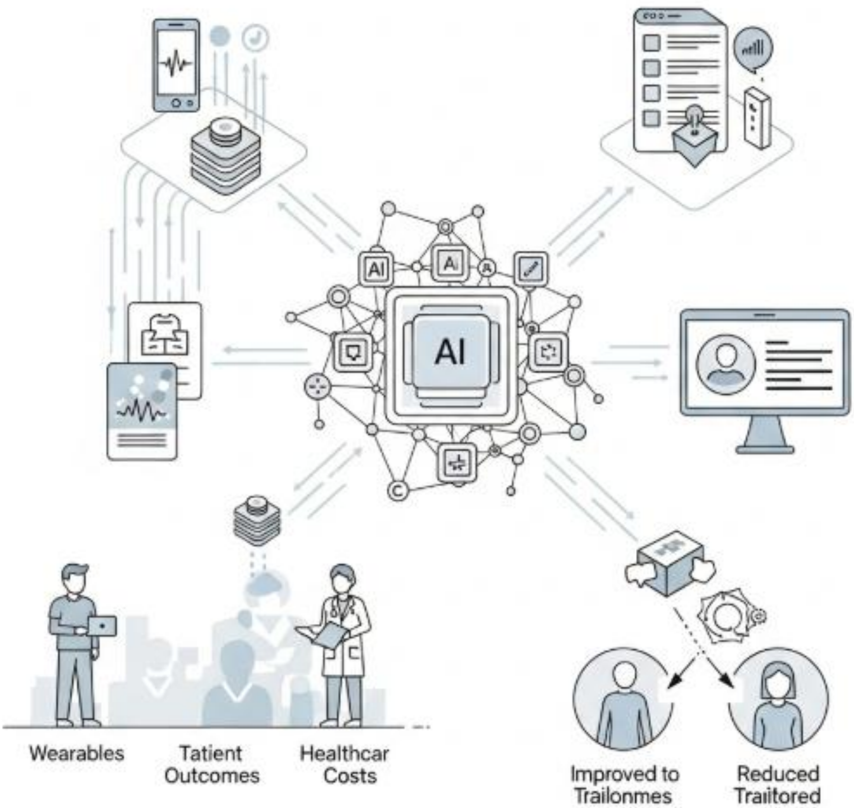

Fig 8.1: Creating Predictive and Personalized Care Models

8.2. Overview of Healthcare Data

Healthcare is increasingly driven by data, especially as we head towards a connected value-based model, with focus on the right care at the right time, delivered at the right location by the right provider for the right patient. Data is available from a variety of different sources and types, including unstructured and human generated. Over time, this data is being increasingly harnessed by organizations. Data-driven solutions are emerging targeting various areas of predictive and personalized healthcare, changing the paradigm around even the most complex of diseases. This chapter provides an overview of healthcare data types and sources, provides some key insights on them, and discusses their applications.

Healthcare data, both structured and unstructured, is generated and consumed from multiple sources across various stakeholders in the healthcare ecosystem including patients, payers, providers, researchers, pharmaceutical and device companies, and regulators. Over time, these organizations have invested in creating and curating their data archives, which need to be sourced in an appropriate manner, de-identified, processed, harmonized, and integrated to be able to get the true value from them.

8.2.1. Types of Healthcare Data

The healthcare industry recognizes different types of data that can be collected and analyzed to enhance the health and healthcare of individuals. Each of these types stems from a different purpose, focus, structure, and mechanism. Some are only used in research or specialized settings, while others are more commonly used in primary care and daily life. The healthcare data landscape can be broadly examined from two points of view. One point of view is based on type and source; another point of view is based on whether it is being used for treatment, payment, or policy-making/enforcement. In this review, we discuss types of healthcare data based on source data.

Experimental sources are utilized in clinical research to develop new drugs or treatment plans. Often, this includes extensive genetic, pharmacogenomic, microeconomic, and some phenotypic data originating in randomized clinical trials. For instance, with human immunodeficiency virus, we would expect to collect demographic data, pertinent history, information about acquired risk factors, clinical and laboratory data, and results from testing for other sexually transmitted diseases. Multi-site networks have recently been developed to allow mining of large integrated databases such as market basket databases and electronic medical records databases.

The FDA encourages sponsors to collect and submit data from a variety of sources, including observational data, to supplement clinical trial evidence to assist with new drug approval and new drug application labeling. Electronic health records, Device

Registries, the Manufacturer and User Facility Device Experience Database, Public-Private Partnerships, Post approval studies, Post-market surveillance, Utilization and claims databases. Traditionally, administrative claims data were the main source of economic information on drugs. The largest such database consists of claims for all services provided to over 55 million persons sixty-five years of age or older enrolled in Medicare.

8.2.2. Data Sources in Healthcare

While healthcare data is typically classified according to its type (such as metadata and actual data, clinical and non-clinical data, structured and unstructured data), it can also be classified according to its source. This classification is vitally important for predictive and personalized models, as models using data from a limited number of sources are less explanatory and explanatory power is directly related to their validity and utility. Within this classification, healthcare data can be considered in three main sources or silos: hospital-reported data, patient-reported data, and non-reporting data.

Firstly, hospital-reported data are provided or computed by hospitals, payers, and other institutions regarding the care provided within their systems. These data types generally have adequate quality, being produced and followed by healthcare professionals who carefully apply standardized methods to record most procedures. However, hospital-reported data generally provide care information from a limited time span, mainly concerning healthcare services delivered only in hospitals. Data from this source is particularly appropriated for predictive models, such as readmission risk or care cost. However, when exploring endpoint occurrences, such as health state deterioration or the occurrence of unintended effects, exclusively using hospital-reported data may provide highly misleading results due to the healthy-user bias. This bias consists of the healthy being more prone to use only ambulatory-care services provided by hospitals or, even more frequently, none of their services. As a result, endpoints that are not being monitored outside of hospitals during the out-of-hospital periods can be overlooked.

8.3. Artificial Intelligence in Healthcare

Advancements in computational capabilities have enabled healthcare to leverage the application of AI-based models for medical diagnostics, clinical decision making support, medication management, and medical document management. The healthcare domain is increasingly generating sensitive patient data in healthcare databases and electronic health records. These high-volume heterogeneous datasets possess sufficient characteristics and are available for training predictive models, prompting potential researchers to focus their attention on healthcare solutions. Machine Learning is a subfield of AI, which is capable of identifying patterns in the enormous volume of available data, and thus provide more effective decision making support systems suitable for intelligent healthcare solutions. The application of AI in healthcare is progressively becoming an active area of research and development due to the availability of large datasets, which offer a foundation for training analytical, interpretable, and prediction models by superior ML methods.

Fig 8.2: Artificial Intelligence in Healthcare

Some of the earliest applications of AI in healthcare included the use of expert systems developed for specific domains. Knowledge-based expert systems were developed in attempts to provide diagnostic decision support, and these systems consisted of a knowledge base that held domain knowledge, and a reasoning engine that processed the given facts for making inferences. An expert system was developed to supply clinical decision support for diagnosing haematological malignancies. Another knowledge-based expert approach was used to assist in the diagnostic support of acute hepatobiliary disease. The vasculitis clinical expert is also an expert system developed for providing a diagnosis in cases of small-vessel vasculitis. All these early expert systems are based on traditional logic programming, or hard-coded rules which are usually incapable of intelligent behavior or self-learning.

8.3.1. Machine Learning Applications

In recent years, healthcare technologies have increasingly begun to focus on utilizing artificial intelligence (AI) and machine learning (ML) techniques with the goal of improving overall patient outcomes. Such systems have emerged to manage workflows, increase diagnostic accuracy, and reduce the number of unnecessary tests and procedures. Other types of machine learning applications designed for healthcare seek to improve patient experiences by increasing patient engagement, improving health literacy, and providing predictive and personalized care pathways to patients. More traditional clinical functions–such as diagnostic and therapeutic decision-making, prognostication, and disease identification and classification–have also embraced machine learning to varying degrees. In effect, AI has been applied into nearly every aspect of modern healthcare.

Some of these applications have already begun to realize impact and value at scale. AI-powered diagnostic imaging solutions are improving the accuracy and speed of pathology, dermatology, ophthalmology, and radiology specialists and subspecialists, thereby enabling them to avoid more mistakes and serve more patients. AI-driven patient experience management systems are helping hundreds of millions of patients better understand their care pathways, navigate the healthcare ecosystem, and meaningfully engage with their care teams. Virtual health assistants powered by AI conversational technologies are being deployed to enable HCPs to concentrate on more complex patient needs, as well as enhance patients' overall health literacy, engagement, and experience. Predictive and prescriptive AI algorithms used to inform care pathway design and monitor patient statuses are assisting HCPs in determining when intervention is required, thereby enabling timely care interventions and improved overall outcomes.

8.3.2. Natural Language Processing

Natural Language Processing (NLP) is a subfield of AI that deals with the understanding and generation of human language. It can analyze data in unstructured format like patient reports, conversations, social media, or support team interactions by using algorithms. NLP tools can judge the sentiments or emotions behind the words as well as derive the intent and insights from these. Whenever we search for something or ask a virtual assistant to do something for us, we are using NLP. It is so ubiquitous that we hardly think of it as it is part of our everyday interaction with technology nowadays.

NLP has a broad range of healthcare applications in analyzing information provided in clinical notes, Electronic Health Record (EHR) notes, and social media accounts, code assignments based on clinical notes, the doctor-patient conversation both in a clinical environment and through teleconsultation, clinical decisions support systems, patient's emotions monitoring and sentiment analysis through voice analysis, speech recognition, understanding the intent behind care teams Diagnosis and Treatment Actions or any other Questions during the patient journey, patient's directed care plan with social determinants using chatbots, deciphering the privacy level concerns based on patient notes or conversations using voice, summarizing urgent patient notes that are usually made very quickly during emergency or acute care situations, and reducing healthcare claims and denials through the patient interaction interface or chatbots.

8.3.3. Computer Vision in Medical Imaging

Computer vision using deep learning auto-encoders or convolutional neural networks is being increasingly used in medical and healthcare image analysis. Deep learning, a subset of machine learning, has recently been heralded as a great technology for a variety of tasks including the use of large datasets commonly used with images. Computer vision using deep learning for medical data is used for detection, identifying lesions, segmentation, alignment of images, generalization across datasets, and domain adaptation. In healthcare, deep learning is rapidly being implemented within cross-disciplinary teams. Companies are implementing a number of applications, generally centering on and considered being solutions to detecting pathology or aberrant lesions from both clinical pathology instruments as well as radiological imaging modalities.

Combining input from many datasets and different modalities allows for generating better model classifiers. Labeling the ground truth involves radiologists or medical image specialists, which may limit the number of various datasets. Rubric-guided machine labeling can be implemented to guide the learning model classifiers to accelerate the speed and automation of these processes. Transfer learning from large annotated video image datasets provides additional guidance in developing specific models from smaller radiological image data. Large datasets can help in mitigating bias, which can otherwise influence model output. Data augmentation is also a technique that can help in overcoming limitations of smaller image datasets – including affine transformations, adding noise, local elastic deformations, and mirroring, among others. Adversarial networks can also be explored to denoise and apply better transfer learning guidance. Cross-domain model transfer and domain adaptation techniques can help in generating better classifiers, which can then be validated with a testing set of unseen patients.

8.4. Predictive Analytics in Healthcare

In recent years, risk prediction has emerged as an increasingly popular method to improve clinical care processes and health outcomes. Hospitals, payers, and regulatory agencies have invested in predictive models to identify patients at risk for negative outcomes, from surgical complications to hospital readmission, intensive care, or mortality. Although some predictive models make use of complex algorithms, like random forests or deep learning methods, many traditional and widely used risk prediction models are based on logistic regression.

Logistic regression is a highly interpretable statistical modeling algorithm that codifies the joint association of predictors with a particular outcome. The resulting prediction model estimates a patient's risk based on a small number of readily available clinical variables. Models developed in this way have been used to generate clinical risk scores for estimating the risk of adverse outcomes in a variety of different patient populations, across many different clinical areas. The most famous of the traditional risk prediction models is the APACHE II score, which estimates the mortality risk for patients admitted to intensive care based on clinical and laboratory information available within the first 24 hours of admission. However, despite the influence of regulatory incentives and growing predilection among healthcare stakeholders toward the use of risk prediction as a decision-making framework, the current state of risk prediction in most areas of clinical practice remains imperfect, particularly with respect to the high false positivity of some popular prediction models.

8.4.1. Risk Stratification Models

Predictive modeling techniques are already applied across a number of clinical use cases, including risk stratification, diagnosis, prognosis, treatment, and prevention. Some of these are already embedded in clinical workflows via clinical decision support systems, such as sepsis and early warning score calculators, or as alerts and prompts within electronic health record systems to facilitate diagnosis and appropriately suggested management recommendations. Others are continuously monitored and inform decisions in practice settings, such as mortality, readmission, and length of stay in hospitalizations. Yet, while typical risk calculators used in practice today remain relevant, their application is typically for only a small subset of patients and rely on a small number of variables extracted via well-defined pathways. Moreover, there is often a considerable delay between estimates and decision-making, given that they are only generated at the time the healthcare provider looks up those scores.

Advances in machine learning, data collection, and storage, coupled with increasing access to computer hardware with GPU accelerators, are changing the landscape for risk stratification in healthcare. Today, it is possible to develop personalized predictive models that can provide updated risk estimates – as often as daily – across entire populations of patients and that rely on large amounts of clinical and social data that are not necessarily collected in a structured manner. Recent work has shown that derived features from clinical notes in EHR can improve risk predictions, especially for rare disease presentations. In addition to being able to detect more complex, high-dimensional interaction terms, deep learning models have been shown to outperform traditional machine learning methods for some prediction tasks, such as readmissions and hospital mortality, particularly when trained on large amounts of data.

8.4.2. Predictive Modeling Techniques

Computational modeling relies on complex mathematical approaches that can increase the predictability and practical applicability of the classifier's and other heuristic and classical statistical methods. In other words, the predictive modeling research field employs computational reproducibility with specific mathematical models thus adopting theoretical computing science paradigms. The use of advanced modeling methods boosts the model's performance and improves its potential usability thus opening innovative strategies in clinical practice. Data available for prediction purposes are generally not complete since there is a limited availability of longitudinal data characterized by the same variable measurements during an extensive period. Consequently, individuals are subject to be censored with incomplete data conveying different information from the others. Clinical events usually occur repeatedly such as a series of comedications or new onset of a disease such as diabetes during a longer follow-up. Beside theory, empirical results state that unobserved heterogeneity influences the association between predictors and outcomes. For instance, we could recall that the likelihood of developing diabetes is higher among specific groups compared to the general population. The review of predictive models in healthcare domains provides evidence on the predictive modeling interests by researchers. It is noted that in most of the investigated healthcare domains the most used approach to predictive modeling is the recursive partitioning, with Decision Trees, Random Forests, and slightly less apparent the Gradient Boosting, usually with some forms of weighted loss functions to overcome the class imbalance.

Research provides evidence in favor of the high performance of ensemble algorithms such as Random Forests and Gradient Boosting. In fact, regardless of the study design, whether it is based on real world, retrospective, or prospective data, the comparative advantages of ensemble algorithms persist. Of course, not always nor everywhere. Specialized predictive algorithms have been developed within domains providing significant advantages. For instance, in the case of predicting a spatio-temporal, normally resident in the metropolis, or sensitive to spatial heterogeneity and Vibroacoustic Pollution, specialized predictors such as geographically weighted regression and deep learning emerge as a victorious choice.

8.5. Personalized Medicine

Advances in healthcare technology and treatments have made it possible to tackle many chronic conditions, leading to improved patient prognoses and quality of life. Care pathways for these patients often involve several specialists and considerable amounts of healthcare resources. In the past few decades, a key shift in how care models are approached is the emergence of patient-generated data to explain the progression of chronic diseases over time. Digital health, genomics, and pervasive computing, among other forces have nudged toward putting the patient at the center of the care model. The move from equitable ordering of treatments, where populations are treated based on the best evidence for them, to personalized medicine reflects the need for patients to be treated as unique individuals and empowered health care actors. This move is accompanied with the increasing use of precision medicine approaches, which entails the advancement of treatments and modeling pathways based on health, social, and genomic situations.

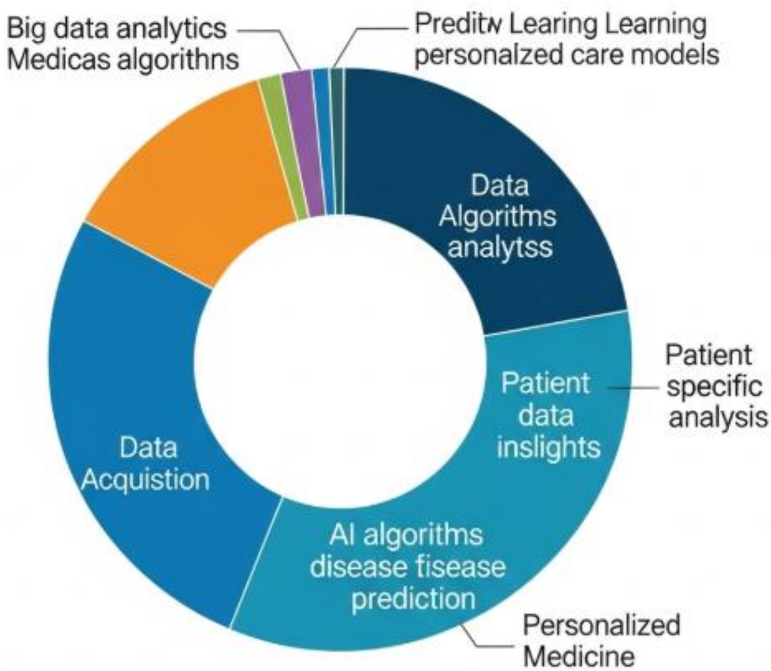

Fig 8.3: The Intersection of Data, AI, and Healthcare

Personalized care models focus on developing specific treatments based on subgroups of patients and also on identifying unique interactions within patients. Rare conditions, such as Bournevill's, can benefit from personalized models as well as more prevalent conditions, such as lung cancer. Progress toward patient-empowered care has fostered the growing use of wearables, sensors, applications, and other data-enabling tools to track health, activity levels, sleep, isolate shocks, and monitor worsening or recovery. Personal health records support patients in consolidating their information from different providers in order to help effectively manage their health. Ultimately, shared decision-making, patient-initiated interactions with trusted providers, and remote-enabled care delivery, grounded in robust health data interoperability between patients and providers, is the underlying principle of personalized medicine.

8.5.1. Genomic Data Integration

The predictive models discussed in the previous chapters can derive individual characteristics such as age, geographic location, or pathology from auxiliary clinical records but cannot explain the biological basis of interindividual differences in the response to illness, therapy, and the risk of adverse events. To deal with the cellular and molecular dynamics that differ among healthy subjects, patients, and responders or nonresponders to therapy, it is necessary to extend capabilities by integrating genomics, transcriptomics, and/or proteomics and metabolomics data.

In the past few years, sequencing-based technologies have unlocked a remarkable innovation pace in the acquisition of genomic, transcriptomic, protein, and metabolite data. Nevertheless, to date, such data have gained only limited adoption in the context of personalized medicine, and predictive and descriptive models in clinical and biomedical research remain mainly based on the integration of auxiliary clinical record data. At the same time, many models aiming to support physicians in unraveling useful information on the biological state of patients or healthy individuals through the integration of omics data have been developed. These data, however, may represent a hallmark of the disease rather than an adequate tool to characterize the actual and dynamic biological processes affecting the individual at the time of tissue or bodily fluid collection. Additionally, the models developed for gaining insights directly from the omics data have not entered routine clinical practice nor are they applied in the context of data integration techniques.

8.5.2. Tailored Treatment Plans

Every person has specific genes, proteins, and other biological factors. Additionally, environmental factors such as geography, climate, and local living conditions can vary between people, often affecting disease progression or symptoms. Personalized medicine aims to develop medicines tailored to the individual genetic characteristics of patients, leading to more effective treatment with fewer side-effects. By understanding these individual factors, personalized medicine can help physicians develop a more effective and suitable treatment plan. The effectiveness of existing treatment plans can increase through personalization. Recurrent respiratory diseases generally accounted for most hospital readmissions. In order to reduce their recurrence, a number of respiratory doctors developed a tailor-made plan for some patients with prediction-based high risk. For this, the number of prediction-based high-risk patients for recurrent respiratory diseases in the next year was identified by using an artificial neural network. The prediction model was developed by adopting the risks of age, sex, admission season, Charlson comorbidity index, sub-discharge diagnosis, and smoking pack year. The features were selected by random forest recursive feature elimination analysis and optimizing the algorithm parameters with a grid search technique. Then, the high-risk patients were discharged with a personalized-tailored management plan using specific anti-infection and rehabilitation intervention supplies. Thus, the tailor-made respiratory management program decreased annual hospital readmissions through improving disease symptoms, preventing or shortening the hospital-discharge time during airway infection caused by COVID-19, and making patients turn to a stable group. Furthermore, the program could also accelerate their rehabilitation even if they suffered severe COVID-19 by using antiviral agents and immune regulation in the rehabilitation process.

8.6. Ethical Considerations

While the promise of predictive and personalized care is exciting, it's important that healthcare organizations are vigilant in protecting against the associated ethical risks. Data privacy, security, and algorithmic bias are priorities as AI crosses the patient-physician relationship threshold. Especially when it comes to health information, trust is our value currency; we must subscribe to the principle that we must do no harm with the data that patients so generously share in exchange for better outcomes. Specifically, we refer to the ethical considerations of patient data privacy, concerns over the security of sensitive health data, and bias in AI algorithms. We need to keep data private, secure it safely, and use it in a way that does not propagate inequities.

As medical AI applications scale to model more nuanced patient interactions, we will need to be more cautious of the sensitivities of health data and its use. Patients who lend us their health data, the sensitive private histories comprising astonishingly varied lifetimes, deserve assurance that we will keep them safe from exploitation. At the most contemporary pivoting point during the Pandemic of 2020, patients were simply hungry for information. Trusting healthcare organizations with their data as they voluntarily signed up to get notifications for tests through contact tracing, they were unknowingly putting themselves in precarious situations of being geo-tagged for a potential virus.

It is at this very moment where several unauthorized private companies were just a few seconds away from creating harmful implications with this data. Just a few weeks after the first news report on the outbreak came out, a private software and data analytics company specializing in geospatial imagery revealed that it had obtained data from a specific location outside the initial outbreak and referenced a previous data breach to advertise its proprietary technology to track population movements.

8.6.1. Data Privacy and Security

Artificial intelligence is revolutionizing health care delivery. AI can provide insights from disparate data generated by ongoing interactions of diverse stakeholders inside and outside the healthcare ecosystem. Engagement with the proposed predictive and personalized Model of Care for Everyone, Everywhere, is necessary to fortify it. This interaction entails modern clinical practice, continuous patient–Provider interaction, advances in communication technology, growth of healthy communities, remote consultations, monitoring and management, provision of enabling devices and materials, and an engaged patient–Provider community. Non-Health-care stakeholders, including those offering transportation, education, social engagement, and financial support services that promote and sustain Health Equity need to be integrated into the Model. Each of these key stakeholders in health care systems generates and utilizes an enormous quantity of data. Large-scale clinical, trial, operational, and comparative-effectiveness data generated in an immersive healthcare ecosystem characterize the individual and population during disease management journeys. That data can nourish AI engines with an ongoing supply of rich, high-quality information, allowing the AI or ML model to continually refine its intelligence.

AI algorithms built with training data that include diverse demographic populations including race and ethnicity, international and regional origin, persuasion, age, sex, gender, comorbidities, disease etiology, and outcome, can generate predictive models for Health Care Equity. AAI solutions for the management of the health care system and disparate vulnerable populations can carve data privacy roadblocks. Any robust technology needs to provide a framework for ethical data privacy and security. Trust in the technology can be engendered by employing contemporary cybersecurity protocols, maintaining confidentiality, ensuring accountability, transparency, accuracy, diversity, and reliability of the AI data processes, and providing recourse to stakeholders deprived of on-demand access to their data.

8.6.2. Bias in AI Algorithms

Data-driven personalized healthcare solutions carried out with AI algorithms could lead to further existing inequalities in treatment access. Most importantly because of earlier biases incorporated during the data selection phase, which results in the presence of known biases in algorithm design. These biases arise from taking a potentially incomplete perspective or an incomplete set of persons into consideration. Some people might not be represented at all in the datasets or only in small proportions. Biases may also be deliberated in terms of negative representation, as a set of features could have negative weighting in resolution in terms of prediction or intention evaluation. In other words, an AI application may highly disfavor a certain category based on historical data. This disregard or negative weighting could be dictating if they were misrepresented in earlier decisions made based on results from AI.

In the healthcare sector, these decisions could have dramatic effects by failing to predict possible risks in areas such as overdose or birth health, in which certain groups are underrepresented. Bias mitigations throughout the entire learning process may help to avoid unfair performance in the trained model. Before the design of AI algorithms, selection bias or exclusion bias should be considered. By including the most diverse and broad cohort of participants such as various ethnic backgrounds and even differing risk sets, some bias influence can be prevented by the research team. Furthermore, to optimize utilization of algorithmic support, excessive imbalance should also be avoided because creating biased models with the intention to decentralize healthcare research across broader demographics could have numerous severe implications in live-or-death situations within disease treatment and therapy response prediction.

8.7. Conclusion

There is much potential for the future development of predictive models in healthcare and also clearly a need. However, so far, collecting and utilizing big health data for predictive modeling application has proceeded in an ad hoc manner, without sufficient guidance, consensus, or proven methodology. Very little has been published or discussed, yet a significant number of predictive models have been or are being created and utilized, particularly by hospitals. The question of how to streamline this process so that predictive models are easier and faster to create while also being more reliable and reusable has not been sufficiently explored professionally. The workplace, especially if it applies to some computerized or cloud-based modular system, is not so simple considering all the stakeholders, but it should be.

Building better predictive models is costly, computationally long, and time-consuming work, using complicated fields yet should be easier, not harder. The future of predictive modeling in healthcare appears to lie in further democratization of model creation and deployment. That is, predictive modeling software should use multi-case modeling environments that are usually intuitive to most average data experts. In addition, concepts from the AI automated machine learning field should be factored into the modeling, suggesting the need to build models in a standard but creative way. However, the social and financial complexities of making predictions seem arbitrary and the urgency of decision-making must all be taken into account.

8.7.1. Future Trends

As the world evolves, so do the opportunities and challenges in the intersection of data, infrastructure, artificial intelligence, and personalized and predictive healthcare. Technology promises to enable novel methods to analyze healthcare data, build models to predict or prevent diseases and illnesses, and create personalized treatment, healthcare and service models. Sophisticated novel models are being developed leveraging advanced and deep learning techniques using large-scale unstructured data – such picture images, videos, text, and voice data. The democratization of these AI technologies suggests that the ultimate outcome could be AI-based screening programs for early detection of diseases such as diabetes, dermatopathologist, cardiac diseases, and others, leading to predictions based on individual anomalies; programmable and personalized healthcare; democratized healthcare services delivery leveraging AI assistance; automation of healthcare documentation; and enhanced clinical decision making.

The practical implementation of this vision, however, introduces some challenges. Acting upon predictions made using foundational datasets when diseases are not present involves risk of bias and possible ethical and reputable ramifications. Moreover, regulatory and compliance issues need to be addressed to access the foundational datasets. AI provision of clinical decision support is in some sense an augmentation of the healthcare professional's capabilities. The ultimate success of this collaboration relies on training – the ability of the systems built to identify valid patterns in healthcare data, and of the healthcare provider to properly leverage the system's models with the broader patient-specific context. Enhancing both capabilities for various use cases is likely to lead to successful collaboration – and, consequently, useful and possible gamification-based ML applications leading healthcare professionals to readily obtain clinical AI insights.

References

Ahmed, E., Rehmani, M. H., & Chen, J. (2018). Mobile edge computing: Opportunities, solutions, and challenges. Future Generation Computer Systems, 70, 59–63.

Taleb, T., Samdanis, K., Mada, B., Flinck, H., Dutta, S., & Sabella, D. (2017). On multi-access edge computing: A survey of the emerging 5G network edge cloud architecture and orchestration. IEEE Communications Surveys & Tutorials, 19(3), 1657–1681.

Shuja, J., Gani, A., Shamshirband, S., & Ahmed, E. (2019). A survey of mobile edge computing: Architecture, applications, and approaches. IEEE Access, 6, 78087–78105.

Kumar, N., & Mallick, P. K. (2018). The Internet of Things: Insights into the building blocks, component interactions, and architecture layers. Procedia Computer Science, 132, 109–117.

Ghosh, R., & Das, S. K. (2019). A survey on smart grid communication infrastructure: Motivations, requirements and challenges. Computer Networks, 108, 111–133.

.