ANALYTICS FOR PATIENT CARE: HOW AI IS USED TO PREDICT PATIENT HEALTH OUTCOMES AND IMPROVE CARE PLANS

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ABSTRACT—This paper will extensively discuss how predictive analytics and various artificial intelligence (AI) technologies are currently being utilized in patient care to substantially enhance diagnostic and treatment modalities, while examining some of the major barriers hindering their widespread adoption. It is anticipated that artificial intelligence and machine learning will unequivocally revolutionize healthcare, completely transforming the manner in which we diagnose and treat patients.. Precision and efficiency in the delivery of healthcare will significantly grow as health data great volumes are put to use with technology. AI could potentially bring a revolution in health care having numerous benefits to both patients and providers moreover by taking care of patients in the most effective way and by decreasing the dissatisfaction levels among patients and health care providers. Nevertheless,It must be admitted that those analytics provide a number of drawbacks and risks for patients both them and healthcare providers. Since this field is fast changing, one should accept the fact that much of the data available is a hypothesis that is based on the supposed use of these tools and findings from studies that were conducted on a small scale. The future of this technology is imminent, and more comprehensive surveys will be required to clearly identify both the positive and negative repercussions of such tools on patient outcomes. The spectrum of applications of machine learning in the area of improving patient care is extensive and growing. The predictive models could be created to find out and suggest adequate treatment for patients classified as of elevated risk to adhere to future failures. For example, some of the authors' team has worked on a machine learning tool for community nurses to use for identifying patients at risk of going to nursing homes and craft preventative interventions by this early detection [1]. On the other hand, the predictive models can influence the shared decision-making about treatment options since they predict the effects of the different interventions on future patients` outcomes. This application has been specifically demonstrated by authors as well who have developed a model to forecast the risk of developing chronic arthritis as well as its effects through the long-term, with the purpose of helping people with early inflammatory arthritis to decide whether to start methotrexate. There are a range of ways in which machine learning and AI could contribute to these goals, from predicting patient admissions to informing the delivery of tailored, cost-effective, and clinically effective intervention.

Keywords— Healthcare, machine learning, care, clinicians, analytics, HIPAA, Medicare, telehealth, hospitals, technology, artificial intelligence, algorithms.

I. INTRODUCTION

Adaptive analytics have been transforming today's the healthcare industry to enable doctors to predict patients' chances of getting ill and find out the most effective treatment tactics. The sheer volume and diversity of patient data which comes from electronic health records, sensors, and other technologies has provided a substantial amount of information that is used by physicians in their quest to better predict and understand the health of their patients. Unlike standard statistics, data mining enables capturing unique and valuable information among large loads of different data sets[1;2]. The techniques are the tools which classify data points and reveal cause and effect relationships between the variables. It gives access to the data mining discovery that allows patients to develop data patterns that can be used as predictors of health outcomes and as improvement of care plans. Simulation is the most effective strategy in case of such things as health outcomes of patients and is a kind of imitation of the real process that serves as a testing tool for whatever variants of situations people could imagine. The simulation was employed by many of its applications in the forecast modeling of long-term diseases. In particular, clinical disease state models have been modelled as Markov models to predict the progression of disease and likely outcomes from several intervention strategies. The Holmes and Blamey study that created a Markov Model to predict the advance of Alzheimer and how donepezil works on it has been published in the literature [3]. It offered a visual representation of drug effectiveness in combating the course of the disease and the expenses that correlate with the expected outcomes. Donepezil was found to be cost-effective, and so decision-making could be made based on these forecasts accordingly.

Besides, consistently a time, the data in the process of and intended for analysis merely serves as a historical record of more data. For example, when working with patients in intensive care units, the Pittsburgh study focuses on analyzing lactate data for these individuals. However, it's important to note that this analysis is only a small part of the extensive data that is regularly recorded at specific intervals[4]. The main goal here is twofold: first, to develop and improve methods that can quickly identify and highlight important changes in the data that relate to the patient's condition. And second, to use the insights gained from the analysis to come up with practical recommendations or even automate actions. Interestingly, achieving all of this with high accuracy and precision is possible by wisely using advanced techniques in artificial intelligence and machine learning.

Disease diagnosis can be utilized as a reliable prediction model whereby the disease symptoms are taken as input parameters, and the corresponding disease name is obtained as the output result. Expanding on this notion, the prediction system can be extended to encompass the determination of the most suitable treatment therapy. To achieve this, the input and output variables would encompass the various types of treatment options available and the corresponding efficacy measures for each therapy. A remarkable advancement in this field is the development of the Remote Patient Access Tool (RPAT) by the esteemed MD Anderson's Cancer Centre. This innovative tool serves as a predictive and decision-supporting mechanism, revolutionizing the medical landscape. Within a mere 6-month period since its initial release, RPAT has garnered immense attention[4]. Astonishingly, over 4500 treatment plan decisions have been extensively reviewed, yielding highly promising outcomes concerning patient satisfaction and garnering positive feedback from referring physicians[4]. The future for disease diagnosis and treatment appears incredibly bright with the integration of such cutting-edge technologies.

One of the most natural and intuitive applications that has been discovered is the diagnosis of diseases in the human body. Over time, numerous highly advanced computerized systems have been developed and innovated, specifically designed to accurately diagnose various diseases in humans through the utilization of artificial intelligence (AI) and machine learning. This remarkable innovation is primarily due to the fact that AI and machine learning are exceptionally proficient when it comes to prediction systems [5]. The cornerstone of these systems lies in the fact that decisions are made based on meticulously analyzed and processed data. Consequently, the more extensive and comprehensive the available data, the higher the precision and accuracy of the diagnostic decision. Considering the realm of medical science, a vast and ample abundance of data is accessible, encompassing an extensive range of diseases and ailments. The vastness and diversification of this data contribute significantly to the unparalleled accuracy and effectiveness of these AI and machine learning-based diagnostic systems.

Implementation of AI and machine learning can be referred to as incorporating the latest applications of human intelligence into designing and creating intelligent computer systems. One of the simplest human intelligence process examples is learning, decision-making, understanding, problem-solving, and reasoning. AI and machine learning are increasingly used in computer systems to make it more probable to find solutions for problems that did not explicitly define how they should be solved. This allows computers to adjust, change and develop according to the data or their own experiences [5,6]. AI tools and machine learning allows computer systems the ability to understand, detail, analyze, pattern recognition, informed predictions, and smart insights. This game-changing science can be a driving force behind major disruptions that facilitate hands-free machinations in the sphere from healthcare to finances, transport and entertainment. The AI and machine learning evolution has created a huge number of new opportunities and inspired a global wave of innovation [6]. With the progress of AI and machine learning researchers, developers, and entrepreneurs, we can expect more innovative and practical applications to emerge transforming the world we live in.

II. RESEARCH PROBLEM

The main research problem is to give a review of analytical functions of machine learning in improving patient care, and then present a more detailed explanation of principles and methods. AI analytics has been applied in the study [6] as a technique of identifying the best treatment plans for an individual through recommendation of certain treatment regimens. However, the AI techniques employed in this research work represent only a subset of what we consider to be the wider field of analytics in health. Therefore, we consider analytics in health to be any computational, statistical, and operations research methodology that aims to provide knowledge to inform health decision making. This contrasts with the AI approach given by W.J Fokkens, where he suggests that computers will learn from data and then apply that acquired knowledge to the data to come up with decisions [7]. In some instances, this data-driven approach might be the sole methodology used in an analytics study. In others, the use of formal decision theoretic or optimization models to derive and recommend best decisions can be viewed as part of applied analytics. At a more complex level, it may involve learning and simulating the complex causal relationships that exist between treatments, patient outcomes, and various determinants of health. The importance of making rational and evidence-based health decisions has become increasingly apparent in the new millennium. With rising healthcare costs, the growing burden of chronic diseases, and aging populations in many countries, health services and clinicians are under increasing pressure to 'do the right thing' and provide the best care [8]. Despite having a vast array of potential options available, often it is unclear what the best course of action is for many clinical and health system problems. Informed by the work of clinical epidemiologists and health economists, operations research and decision sciences methods are now being employed to tackle these problems and to provide guidance on how best to improve patient outcomes given the resource constraints under which modern health services operate. This is the niche to which our wider definition of analytics in health is targeted.

III. LITERATURE REVIEW

A. PREDICTIVE ANALYTICAL MODELS

The predictive analytics model would use the abstracted data to produce a 'dashboard' that would advise caregivers on treatment strategies and expected outcomes for proposed care of the patient. This would be a direct attempt to change the current prediction of outcomes model, as doctors may not always be aware of the potential outcomes for patients with certain courses of treatment. While this could prove to be a very beneficial model, the reference study of regression models for predicting death compared to hospice care showed that positive explanatory power is not likely, as the future care decisions were not predictable. Machine learning models predicting health outcomes for the elderly have been studied as a means to predict the future progression of disease for certain patients to better plan long-term care strategies[9].

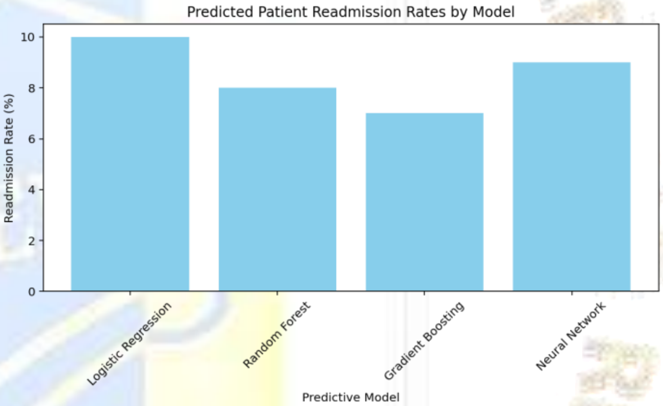

Fig. 1 Predicted Patient Readmission Rates by Model

Another article published cited here, in the development and application of unsupervised learning methods in a dynamic and familial context, to predict the evolution of AD or related dementias for the purposes of comparing future care scenarios, Alzheimer-specific health outcomes, and health economic implications. This would likely show varied results and many ethical questions in regard to informed consent for future decisions and determining a point when detrimental treatments should be stopped. Both of these models would be attempting to predict potential health outcomes and aim to suggest the best future care plan for the patient. This can be said about much of AI in patient care. Should it achieve its goals in aiding decision making and providing potential care directions, it will largely shift the paradigm of many care scenarios with some mixed results [9]. A study into data mining techniques for determining a care plan for COPD patients showed that the decision tree can be used to determine an "optimal sequence of treatment decisions to achieve a certain clinical goal," which in the context of the study would determine a long-term or end-of-life care plan to decrease the rate of hospital admissions. This would be a very positive result but raises questions about the effectiveness of future treatments compared to a predetermined goal. Overall, the literature on these AI-based methods to determine patient health outcomes is varied but has some positive results[10]. While it may not be the suited directed change in all care scenarios the pages of time, AI models have variously shown the potential to determine future lapse into palliative care and possibly deterring certain treatments for diagnoses into terminal conditions, and its ability to accurately predict specific health outcomes provides a tool to compare future care scenarios for a given patient with today's best care.

B. Predictive Analytics in Healthcare

In the rapidly evolving healthcare industry, predictive analytics has emerged as a relatively new and game-changing phenomenon that plays an essential and paramount role in improving patient health outcomes. Over the next 5 to 10 years, experts predict that the widespread adoption of predictive analysis will empower healthcare professionals to comprehensively report and analyze clinical conditions over an extended period of time, leading to a revolutionary transformation in the way we approach patient care [10].

Predictive analytics encompasses a diverse range of techniques, including data mining, modeling, and other analytical methods, all aimed at identifying patterns and trends in a patient's health. This can be accomplished by pooling information from a wide-ranging and intricate database, which includes details about multiple factors including clinical issues, comorbidities, gender, lifestyle choices, genetic inclinations and environmental vulnerabilities amongst others. Consequently, by having detailed information, they can use predictive models to segment specific individuals that are at a risk of particular types of health outcomes. Predictive analysis technique involves employing historical data with modern algorithms in such a way that it makes precise and knowledgeable suggestions on a diabetic patient's health status in the future. The identification of at-risk patients related to kidney damage will prompt healthcare professionals to take preventive measures at an early stage through which the complications of the disease can be effectively prevented.

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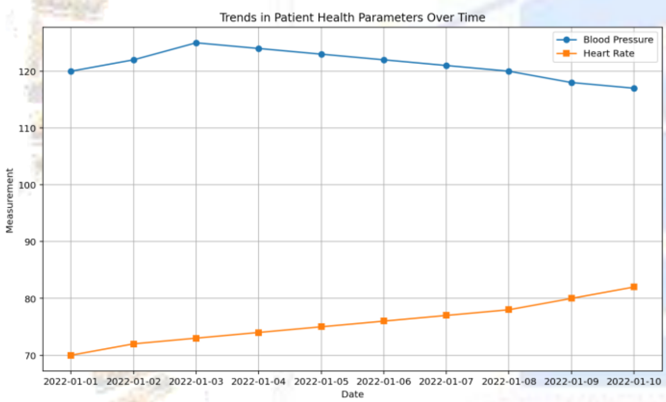

Fig. 2 Trends in Patient Health Parameters Over Time

Moreover, predictive analysis, which has shown to be greatly useful in the management of the chronic diseases in a resourceful manner. Healthcare providers can forecast future health states with specific events and their anticipated time of occurrence, such as myocardial infarction (MI), and take timely and proactive measures to minimize the risks of these conditions. For example, the long-term risk of revascularization is frequently observed by coronary diseases and the disease of diabetes may affect the risk[12]. Should any predictive results indicate the risk of a bad outcome or an elevated chance of a specific health event, the people it affects might be identifies clearly and the risk to the involved individuals duly explained. This extensive comprehension allows for the creation of accurate predictive models that can foresee these events, enabling healthcare providers to fully discuss the positive and negative aspects before deciding what preventive measures to take accordingly based on the expected results.

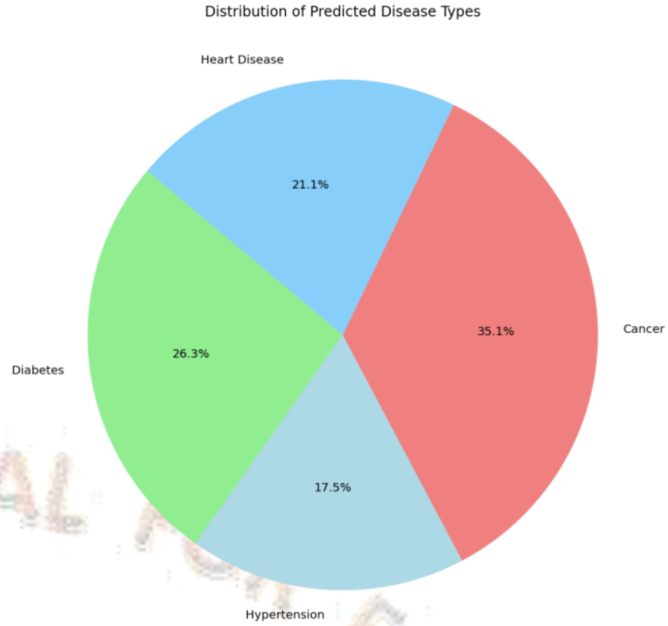

Fig. 3 Distribution of Predicted Disease Types

C. AI in Patient Care

The field of AI in patient care has continued to grow with many varied applications focusing on different aspects of patient care. One example is a recent study by Sendak et al., which used machine learning to predict in-hospital mortality of patients. Data from the electronic health records of 32,000 patients were used to train the model, and it was found that the model outperformed existing state-of-the-art prediction models. Sendak et al. developed a user-friendly web-based platform to input patient data, which would then make real-time mortality predictions to help inform clinical decision making. Another interesting example is a recent study using data mining and machine learning to aid the early diagnosis of Alzheimer's Disease[12,13]. This is done by analyzing the data taken from the linguistic and discourse skills of healthy and cognitively impaired individuals in order to develop an automated classification system.

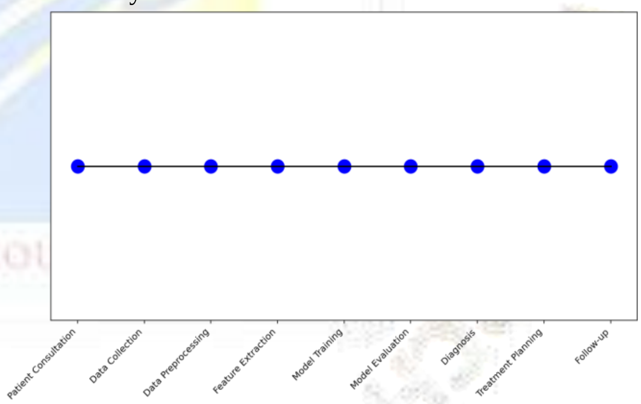

Fig. 4 Workflow for AI-Driven Diagnosis in Patient Care

AI in patient care involves the use of AI methods and techniques (such as intelligent agents, decision trees, Bayesian networks, and machine learning) to determine the best course of treatment for a patient. An early application of AI in patient care was the development of the Dendral program at Stanford in the 1970s. This was used to identify unknown organic molecules from their mass spectra and nuclear magnetic resonance (NMR) data. A similar program called MYCIN was developed at Stanford in the early 1970s to identify bacteria causing severe infections and to recommend antibiotics, with the efficacy of recommendations matching that of infectious disease experts[14]..

D. Machine Learning Models for Patient Health Outcomes

The last method to discuss is the use of machine learning models for predicting the likely outcomes of given patients. Ross et al. (2006) provides an example where the Sequential Organ Failure Assessment (SOFA) was used to define sub-phenotypes of critically ill patients. Patients categorized as having a cardiovascular dysfunction without failure were 84% likely to survive while those with malignancy and sepsis with acute organ dysfunction were only 4% likely to survive[14]. The study was able to help define the different mortalities of patients with single organ failure syndromes. The aforementioned work by Dietterich on learning to optimize frequently measured outcomes is essentially classification and regression of the best treatment for a specific patient. He describes a broader model for predicting the effects of a treatment and suggests a separate and very large body of work on causal inference in statistics and philosophy. A specific recent example of using machine learning tools for causal inference is when Roberts et al. used propensity-matched a decision tree algorithm to predict which patients with rheumatoid arthritis would best respond to treatment with anti-tumour necrosis factor drugs. Machine learning models are naturally attractive to the notion of personalized medicine, yet they currently show one of the greatest gaps between optimistic results from small scale studies to large scale clinical use[15]. This is in part due to the inherent complexity in constructing and validating the models, but also the need for an evidence-based medicine culture to change to a real clinical culture.

E. Data Mining Techniques in Healthcare

Data mining techniques in healthcare Data mining is the process of analyzing data from different perspectives and summarizing it into useful information. Data mining in healthcare uses the same steps and processes used to detect patterns in data, gain insight, and develop hypotheses that are clinically relevant. These hypotheses can then be used to obtain information and knowledge about diseases effectively. Data mining has monopolized clinical research and is anticipated to spread its usefulness to healthcare quality improvement [15]. Currently, data mining in healthcare is primarily used with administrative data such as insurance or hospital. However, data mining can produce enormous potential benefits that can utilize clinical data to finally create improvements in patient outcomes. There are a variety of data mining techniques that have been identified and used to improve health outcomes. Some of the most popular methods are decision trees, neural networks, automated prediction, and fuzzy logic. Each of these methods has detailed processes that can vary in complexity. Some types of data mining may be more appropriate in varied situations. It is important to understand which method may be best in a specific circumstance to ensure optimal results[16]. For example, a recent study has used neural network analysis to predict patients several years beyond the current time frame. This could be useful in predicting patient-specific expected longevity. However, neural networks are limited to less complex models, and any additional information may only compromise the accuracy of the prediction. Ideally, implementing a prediction would be best achieved using a complex model and intensive data collection and manpower in a limited time frame..

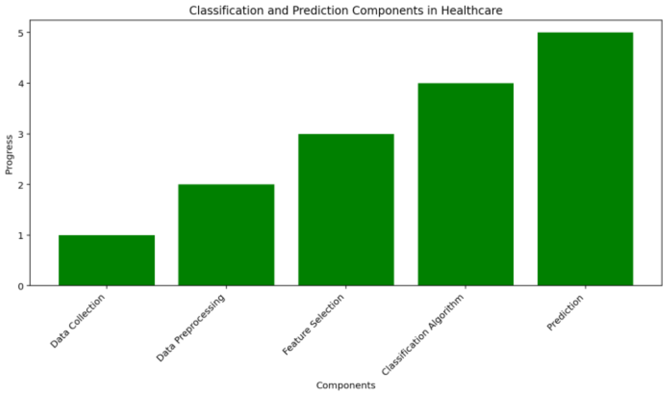

Fig. 5 Classification and Prediction Components in Healthcare

IV. SIGNIFICANCE AND BENEFITS

Using predictive models for simple diagnoses or for flagging potential issues, you can assign risk scores to individual patients based on their likelihood of developing a certain condition. When you're able to identify this risk ahead of time, the possibility of preventative measures increases for healthcare providers, and informed patients are more likely to make changes to their behavior. Predictive models are also used to locate patients at risk of certain conditions to enroll them in disease management programs, in an effort to prevent the condition from developing[16]. By accurately predicting patient outcomes, and the subsequent costs and risks, healthcare providers can take action to correct a negative outcome.

AI has been used to develop and implement clinical support software[17]. This takes the form of alerting providers when clinical events are inconsistent with best practices, suggesting possible diagnoses or treatment options to the physician, or providing relevant information to the patient. Implementation of these systems has been met with varied success, with some studies showing improvement in the quality of care, and others showing no significant effect.

Probably the most widely known AI application in healthcare is the development of IBM Watson. Specifically devised with the intent of using AI to improve healthcare, Watson has been used for various applications, the most widely published being the Oncology clinical decision support system. This system takes input in the form of patient information and provides output in the form of treatment recommendations. A study published in 2012 claims that 90% of all medical data has been generated in the past 2 years, it is no wonder that today there exist hundreds of clinical decision support systems aimed at processing this data to provide a better standard of care[17].

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V. ENHANCEMENTS

The United States is still the leader in healthcare technology, including the usage of AI tools. While it is common for people to use wearable fitness and medical devices to monitor exercise habits and vitals, companies such as Microsoft, Google, and Apple are experimenting with AI applications for diabetics, patients with heart disease, and for patients who have recently been discharged from the hospital. Australia and Europe are also creating and utilizing AI, but the US is noted as having better-developed tools and using the most advanced methods in predictive analysis. In the near future, patients in the US can expect that routine check-ups or visits to the doctor will use predictive tools such as the one used in the diabetic scenario.

Legislation today, such as the General Data Protection Regulation (GDPR) in Europe or the Health Insurance Portability and Accountability Act (HIPAA) in the US, affects how health data is used and influences the development of said laws through data, implying that laws must continue to evolve with technology[19,20]. AI in healthcare is still in early development, but it is evident that technology will continue to progress rapidly. Cases of AI being used to predict the risk of disease will become a routine tool for physicians, and with cloud computing now becoming a common storage system for patients' medical records, predictive tools will have easy access to vast amounts of varied patient data to further improve their accuracy in predicting the health outcome for a specific individual.

There remains an opportunity to reduce costs associated with chronic disease and post-hospital care because predictive AI tools are still in their infancy but showing promise. These tools can be used to prevent diseases from occurring and prevent post-hospital complications, reducing the need to treat such conditions which is much costlier than preventative care. Japan has already seen promising results in using an AI tool to predict the probability of patients developing pneumonia while in the hospital. Reducing costs is also a priority for developing countries, and they could serve to benefit the most as costs can be the biggest hindrance in improving healthcare in such nations[20]. AI is increasingly becoming a larger part of healthcare, and it is crucial that governments and policymakers adapt to the future data-driven approach to healthcare, building the necessary infrastructure to support such tools.

VI. CONCLUSION

The main focus of this review was to assess the roles of machine learning as an analytical tool in improving patient care.Although we are still early in the mobile revolution, the pace of change today is breathtaking. The use of app technology has flourished under the growing pressure for the creative use of technology in healthcare. National policy is now actively encouraging the development of the sorts of technologies presented throughout this paper. The recently published ONC's shared Nationwide Interoperability Roadmap reflects the government's commitment to furthering the development of HIT that serves to improve patient care. The roadmap calls for the identification of existing standards and implementation specifications for a core set of clinical data (the "Urgent Need" first step), and lays out a five-year plan to "create the health IT infrastructure needed to enable a learning health system," with the end goal of bettering outcomes for individuals and communities. This is a tall order, but creating an infrastructure that can evolve individual treatments through the use of comparative effectiveness is a clear match with mobile technology. As clinical guidelines grow more sophisticated, the use of clinical decision support tools at the point-of-care can put new knowledge directly into practice, though advancements are needed in knowing when to deliver what information. High-level evidence will not always have validated an individual treatment, and these tools could fuzzily mimic a supervised learning approach where the treatment becomes the "label" and patient outcomes are continuously monitored and compared with different approaches. High-performance app-based data input and presentation technologies will be demanded to support such decisions given the time constraints and complexity of the patient encounter. All of these IT-facilitated changes to the care process have direct analogs in the realm of medical training, which is another area discussed at length in the context of reforms needed to support mobile tech. Step by step, it is becoming increasingly clear that app technology has potential to align incentives for the provider, the patient, and the technology developer toward the common goal of better health outcomes.

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