

Midocean University

College of Management

Department of Risk Management



Research proposal

The Impact of Artificial Intelligence on Healthcare: the transformation of the practice of radiology in the kingdom of Saudi Arabia in Riyadh

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1.1 Introduction

In recent years, the integration of artificial intelligence (AI) into various sectors has ushered in a new era of technological advancement, and nowhere is this transformation more evident than in healthcare. One particularly groundbreaking area is the practice of radiology, where AI has emerged as a catalyst for significant change. The Impact of Artificial Intelligence on Healthcare, with a specific focus on the transformation of radiology, signifies a paradigm shift in the way medical imaging is utilized, interpreted, and leveraged for patient care.

Radiology, as a critical component of diagnostic medicine, has traditionally relied on the expertise of radiologists to interpret complex images and identify anomalies. However, the advent of AI technologies has introduced a range of capabilities that augment and, in some cases, surpass human capabilities. This evolution not only enhances the accuracy and speed of diagnostics but also redefines the roles of healthcare professionals in the radiology domain.

This exploration delves into the multifaceted impact of artificial intelligence on the practice of radiology, elucidating how advanced algorithms, machine learning, and automation are reshaping workflows, improving diagnostic accuracy, and ultimately revolutionizing patient care. As we navigate the intricate intersection of technology and healthcare, it becomes increasingly evident that the synergy between artificial intelligence and radiology is poised to redefine the landscape of medical imaging, offering unprecedented opportunities for innovation and enhanced clinical outcomes.

While the integration of artificial intelligence (AI) into healthcare, particularly in the field of radiology, holds immense promise, it is crucial to acknowledge and address the accompanying risks. The transformative impact of AI in radiology is not without challenges, and a comprehensive understanding of the potential risks is essential for responsible implementation.

One primary concern revolves around the potential for overreliance on AI algorithms, leading to complacency among healthcare professionals. The technology, while powerful, is not infallible, and there is a risk that clinicians might become overly dependent on automated systems, diminishing their own diagnostic skills and critical thinking. Striking the right balance between AI assistance and human expertise is imperative to ensure optimal patient care.

Privacy and data security represent another significant risk in the era of AI-driven healthcare. As vast amounts of sensitive medical data are processed and stored by AI systems, the potential for

data breaches and unauthorized access becomes a pressing concern. Establishing robust cybersecurity measures and stringent privacy protocols is paramount to safeguarding patient information and maintaining trust in the healthcare system.

Moreover, the introduction of AI in radiology raises ethical considerations surrounding transparency and accountability. The "black-box" nature of some AI algorithms makes it challenging to understand their decision-making processes fully. This lack of transparency could raise ethical concerns, particularly when these systems are used in critical diagnostic decisions. Ensuring transparency, explainability, and accountability in AI algorithms is crucial for fostering trust among healthcare professionals and patients.

1.2 Study problem:

The research problem is that there is an impact of Artificial Intelligence (AI) on the healthcare industry.

1.2.1 The pivotal question

1.2.1.1 To what extent does the impact of the use of artificial intelligence contribute to increasing healthcare risks in radiology practice?

1.2.2 Sub- questions:

1.2.2.1 Identify the extent of the impact of artificial intelligence on healthcare.

1.2.2.2 Identify the most important risks of using artificial intelligence in health care and their impact on the transformation of the practice of radiology.

1.3 Important of the study:

1.3.1 The importance of the research focuses on the impact of Artificial Intelligence (AI) on the healthcare industry. AI has the potential to provide innovative solutions to the long-term challenges faced by the sector, which makes it a significant development. The research examines how AI can revolutionize healthcare in the areas of diagnosis, patient care, and healthcare management. The research also considers the risks and benefits associated with the application of AI and its impact on radiology practices.

1.4 objectives of the research:

1.4.1 The objectives of the research are as follows:

1.4.1.1 Identify the extent of the impact of artificial intelligence on healthcare.

1.4.1.2 Identify the most important city in using artificial intelligence to obtain health data on radiology employees.

1.5 Hypotheses:

1.5.1 The application of artificial intelligence (AI) in the healthcare industry has its advantages and disadvantages.

1.6 Research methodology:

1.6.1 The study will use prospective data. The retrospective data was statistically investigated with Excel. Descriptive methodology is used to analyze the data. The scope of the study is artificial intelligence (AI) in healthcare in the Kingdom of Saudi Arabia during the period between February to April - 2024

1.7 Study tools:

1.7.1 I will use a questionnaire for the research to collect data

1.8 Research location, duration:

healthcare in the Kingdom of Saudi Arabia during the period between February to April - 2024

1.9 Previous study:

Study1

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PMID: [29777175](#)

Artificial intelligence in radiology

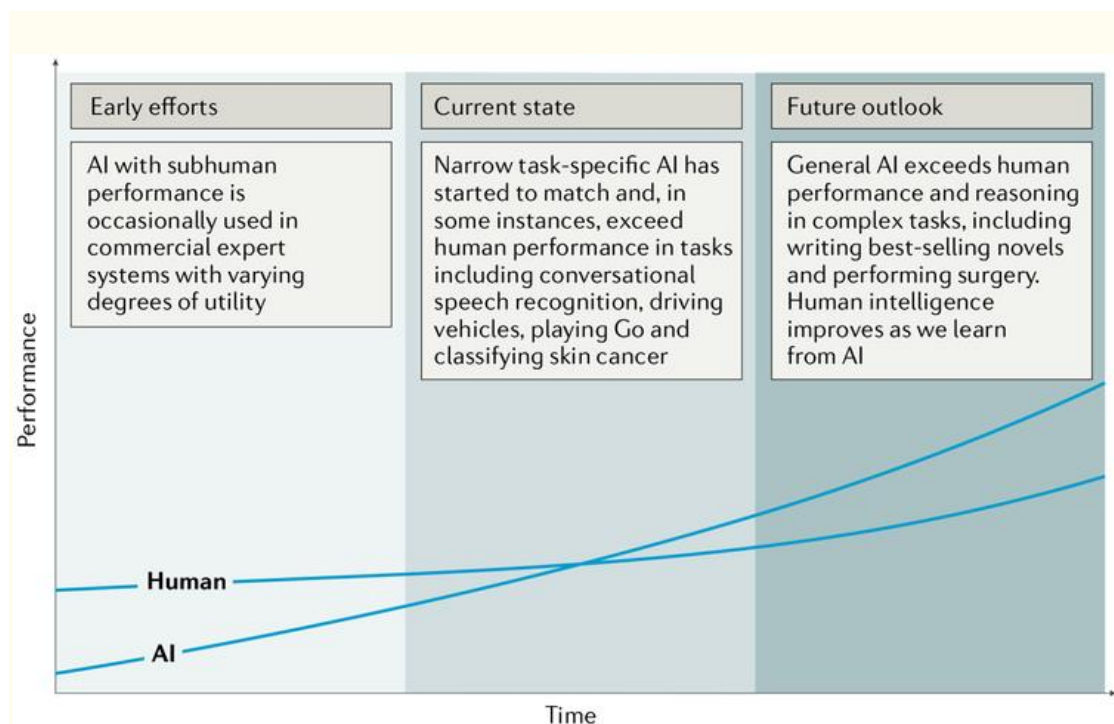
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Abstract

Artificial intelligence (AI) algorithms, particularly deep learning, have demonstrated remarkable progress in image-recognition tasks. Methods ranging from convolutional neural networks to variational autoencoders have found myriad applications in the medical image analysis field, propelling it forward at a rapid pace. Historically, in radiology practice, trained physicians visually assessed medical images for the detection, characterization and monitoring of diseases. AI methods excel at automatically recognizing complex patterns in imaging data and providing quantitative, rather than qualitative, assessments of radiographic characteristics. In this Opinion article, we establish a general understanding of AI methods, particularly those pertaining to image-based tasks. We explore how these methods could impact multiple facets of radiology, with a general focus on applications in oncology, and demonstrate ways in which these methods are advancing the field. Finally, we discuss the challenges facing clinical implementation and provide our perspective on how the domain could be advanced.

Artificial intelligence (AI) has recently made substantial strides in perception (the interpretation of sensory information), allowing machines to better represent and interpret complex data. This has led to major advances in applications ranging from web search and self-driving vehicles to natural language processing and computer vision — tasks that until a few years ago could be done only by humans¹. Deep learning is a subset of machine learning that is based on a neural network structure loosely inspired by the human brain. Such structures learn discriminative features from data automatically, giving them the ability to approximate very complex nonlinear relationships ([BOX 1](#)). While most earlier AI methods have led to applications with subhuman performance, recent deep learning algorithms are able to match and even surpass humans in task-specific applications^{2–5} ([FIG. 1](#)). This is owing to recent advances in AI research, the massive amounts of digital data now available to train algorithms and modern, powerful computational hardware. Deep learning methods have been able to defeat humans in the strategy board game of Go, an achievement that was previously thought to be decades away given the highly complex game space and massive number of potential moves⁶. Following the trend towards a human-level general AI, researchers predict that AI will automate many tasks, including translating languages, writing best-selling books and performing surgery — all within the coming decades⁷.



[Fig. 1 |](#)
Artificial versus human intelligence.

This plot outlines the performance levels of artificial intelligence (AI) and human intelligence starting from the early computer age and extrapolating into the future. Early AI came with a subhuman performance and varying degrees of success. Currently, we are witnessing narrow task-specific AI applications that are able to match and occasionally surpass human intelligence^{4-6,9}. It is expected that general AI will surpass human performance in specific applications within the coming years. Humans will potentially benefit from the human-AI interaction, bringing them to higher levels of intelligence

Study2

[J Am Coll Radiol](#). 2020 Oct; 17(10): 1309–1311.

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PMCID: PMC7164850

PMID: [32360451](https://pubmed.ncbi.nlm.nih.gov/32360451/)

The Potential Dangers of Artificial Intelligence for Radiology and Radiologists

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With the advent of artificial intelligence (AI) across many fields and subspecialties, there are considerable expectations for transformative impact. However, there are also concerns regarding the potential abuse of AI. Many scientists have been worried about the dangers of AI leading to “biased” conclusions, in part because of the enthusiasm of the inventor or overenthusiasm among the general public. Here, though, we consider some scenarios in which people may intend to cause potential errors within data sets of analyzed information, resulting in incorrect conclusions and leading to potential problems with patient care and outcomes.

A generative adversarial network (GAN) is a recently developed deep-learning model aimed at creating new images. It simultaneously trains a generator and a discriminator network, which serves to generate artificial images and to discriminate real from artificial images, respectively. We have recently described how GANs can produce artificial images of people and audio content that fool the recipient into believing that they are authentic. As applied to medical imaging, GANs can generate synthetic images that can alter lesion size, location, and transpose

abnormalities onto normal examinations ([Fig. 1](#)) [[1](#)]. GANs have the potential to improve image quality, reduce radiation dose, augment data for training algorithms, and perform automated image segmentation [[2](#)]. However, there is also the potential for harm if these artificial images infiltrate our health care system by hackers with malicious intent. As proof of principle, Mirsky et al [[3](#)] showed that they were able to tamper with CT scans and artificially inject or remove lung cancers on the images. When the radiologists were blinded to the attack, this hack had a 99.2% success rate for cancer injection and a 95.8% success rate for cancer removal. Even when the radiologists were warned about the attack, the success of cancer injection decreased to 70%, but the cancer removal success rate remained high at 90%. This illustrates the sophistication and realistic appearance of such artificial images. These hacks can be targeted against specific patients or can be used as a more general attack on our radiologic data. It is already challenging enough to keep up with the daily clinical volume when the radiology system is running smoothly. Our clinical workflow would be paralyzed if we could not trust the authenticity of the images and must spend extra effort searching for evidence of image tampering in every case.

There are multiple access points within the chain of image acquisition and delivery that can be corrupted by attackers, including the scanner, PACS, server, and workstations [[3](#)]. Unfortunately, data security is poorly developed and poorly standardized in radiology. In 2016, Stites and Pianykh [[4](#)] performed a scan through the World Wide Web of networked computers and devices and showed that there were 2,774 unprotected radiology or DICOM servers worldwide, most of them located in the United States. To date, there has been no known hack into the radiology system, aside from the research study demonstrating its feasibility [[3](#)]. However, the vulnerability is clearly present and may be exploited by hackers.

Such threats could affect not only radiology departments but also entire health systems. We have all read articles about security breaches of medical records. There have been almost 3,000 breaches (involving more than 500 medical records) in the United States within the past 10 years. This includes high-profile cases such as the 2015 breach of the Anthem medical insurance company that potentially exposed the medical records of 78 million Americans and led to a \$115 million settlement [[5](#)]. Hospitals and clinics have been held hostage when their data were corrupted by a third party that demanded payment (ransom) to release the data [[5](#)]. In 2017, ransomware WannaCry and NotPetya spread through

thousands of institutions worldwide, including many hospitals, and caused \$18 billion in damages [5]. Hospitals and clinics have not been the only targets. The city of Baltimore was essentially out of business for a month this past year because of such a ransomware attack. At first glance, all of these situations seem more likely in a movie made for Netflix or HBO. However, the truth is that we must be prepared to deal with such scenarios in the near future. As electronic health records and hospital data become more centralized and more computerized, the dangers only multiply.

However, there are several ways to mitigate potential AI-based hacks and attacks. These include clear security guidelines and protocols that are uniform across the globe. As deep-fake technology gets more sophisticated, there is emerging research on AI-driven defense strategies. One example features the training of an AI to detect artificial images by image artifacts induced by GAN [6]. However, AI-driven defense mechanisms have a long way to catch up, as seen in the related problem of defense against adversarial attacks. Recognizing these challenges, the Defense Advanced Research Projects Agency has launched the Media Forensics program to research against deep fakes [7]. Hence, for now, the best defense against deep fakes is based on traditional cybersecurity best practices: secure all stages in the pipeline and enable strong encryption and monitoring tools.

In the current coronavirus disease 2019 pandemic, many clinicians and radiologists have turned to working remotely in attempts to “flatten the curve” and slow the spread of disease. In the body imaging division at our institution, currently, approximately half of the radiologists are working remotely. Many of our clinicians are transitioning to telemedicine visits, which adds tremendous stress on our networks. Our IT department has been proactive in setting up a dedicated virtual private network for radiology to ensure that there is sufficient bandwidth for our clinical work. On our few on-site rotations, we practice “social distancing,” and we have suspended our all side-by-side readouts and in-person lectures. We have turned to Zoom (San Jose, California) and other mobile platforms for managing our rapidly changing clinical operations, educating trainees, or simply staying in touch during these uncertain times. The daily meeting participants rose from 10 million daily users in December 2019 to 200 million daily users in March 2020 [8]. Our reliance on Zoom and other mobile platforms has exposed a new vulnerability. There has been a proliferation of “Zoombombing,” in which intruders hijack video calls and paste hate speech and offensive

images. Furthermore, additional vulnerabilities in Zoom can allow hackers to gain control of users' microphones and webcams and steal login credentials. Zoom video meetings did not provide end-to-end encryption as promised, and a large number of Zoom video meeting recordings, many of which contain private information, are left unprotected and viewable on the web. The Federal Bureau of Investigation has issued security warnings about Zoom, and a number of organizations, including SpaceX, Google, New York's Department of Education, and the US Senate, have banned or discouraged the use of Zoom [8]. The meteoric rise and fall of Zoom is a cautionary tale about the importance of data security.

With the development of AI and all its potential wonders in terms of increasing the accuracy of our diagnostic capabilities and potentially improving patient care, we must also be concerned about the potential dark side by bad actors. The sooner organized radiology and organized medicine address these issues with clarity, the more stable and protected the health care system and our patients will be from those intent on creating harm and havoc by abusing AI. The acceleration of data sharing during the current pandemic exposes critical vulnerabilities in data security. It reminds us of the pervasive threat that bad actors can and will exploit any technology for their selfish gains. Doing nothing is not a viable strategy, but acting in a concerted effort will lead us to the protection we need and is important as we push AI development over the next several years.

ومع تطور الذكاء الاصطناعي وكل عجائبه المحتملة من حيث زيادة دقة قدراتنا التشخيصية وتحسين رعاية المرضى، يجب علينا أيضًا أن نشعر بالقلق إزاء الجانب المظلم المحتمل من الجهات الفاعلة السيئة. كلما أسرعت الأشعة المنظمة والطب المنظم في معالجة هذه القضايا بوضوح، كلما أصبح نظام الرعاية الصحية ومرضانا أكثر استقرارًا وحمايته من أولئك الذين يعتزمون إحداث الضرر والخراب من خلال إساءة استخدام الذكاء الاصطناعي. يكشف تسريع تبادل البيانات خلال الوباء الحالي عن نقاط ضعف خطيرة في أمن البيانات. إنه يذكرنا بالتهديد المنتشر المتمثل في أن الجهات الفاعلة السيئة يمكنها أن تستغل أي تكنولوجيا لتحقيق مكاسبها الأنانية. إن عدم القيام بأي شيء ليس استراتيجية قابلة للتطبيق، ولكن العمل في جهد متضافر سيقودنا إلى الحماية التي نحتاجها وهو أمر مهم بينما ندفع تطوير الذكاء الاصطناعي على مدى السنوات العديدة القادمة.

Study 3

Transforming Healthcare: The Impact of Artificial Intelligence

المجلد ١٧، الإصدار ٩، Health Science Journal; Egaleo C, Hainrichard J. (٢٠٢٣). DOI:10.36648/1791-809X.17.9.1064

Abstract

Artificial Intelligence (AI) is revolutionizing the healthcare industry, offering innovative solutions to long-standing challenges. This research article explores the profound impact of AI on healthcare, including diagnosis, treatment, patient care, and healthcare management. We delve into the benefits and challenges of implementing AI in healthcare, its potential to enhance patient outcomes, and the ethical considerations that accompany this transformative technology.

Keywords: AI in healthcare; Medical AI; Healthcare automation; Machine learning in medicine; Diagnostic AI; AI-driven diagnostics

Introduction

The integration of Artificial Intelligence into healthcare has the potential to reshape the entire industry. With AI's ability to analyze vast datasets, identify patterns, and make predictions, it offers unprecedented opportunities to improve patient care, streamline operations, and advance medical research. In this article, we examine the multifaceted role of AI in healthcare and its implications for the future [1].

Diagnosis and predictive analytics

AI-driven diagnostic tools are becoming invaluable in healthcare. Machine learning algorithms can analyze medical images, such as X-rays and MRIs, with exceptional accuracy, aiding in the early detection of diseases like cancer. Predictive analytics harness patient data to foresee disease outbreaks and anticipate patient needs, enabling proactive interventions [2].

Treatment personalization

AI-powered treatment recommendations take into account a patient's unique medical history, genetics, and responses to therapies. This personalization optimizes treatment plans, reduces adverse effects, and improves treatment outcomes, particularly in precision medicine [3-4].

Remote monitoring and telemedicine

Telemedicine platforms enhanced by AI empower patients to monitor their health remotely, and healthcare providers can deliver care more efficiently. Wearable devices, chatbots, and virtual health assistants collect patient data and provide real-time feedback, making healthcare more accessible.

Administrative efficiency

AI streamlines healthcare administration by automating tasks like appointment scheduling, billing, and claims processing. This efficiency reduces administrative burdens, allowing healthcare professionals to focus more on patient care.

Drug discovery and development

Study 4

Artificial Intelligence Transforms the Future of Healthcare

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Abstract

Life sciences researchers using Artificial Intelligence are under pressure to innovate faster than ever. Large, multilevel, and integrated datasets offer the promise of unlocking novel insights and accelerating breakthroughs. Although more data are available than ever, only a fraction is being curated, integrated, understood, and analyzed. Artificial Intelligence focuses on how computers learn from data and mimic human thought processes. Artificial Intelligence increases learning capacity and provides decision support system at scales that are transforming the future of healthcare. This article is a review of machine learning applications in healthcare with a focus on clinical, translational, and public health applications with an overview of the important role of privacy, data-sharing, and genetic information.

Keywords: Artificial intelligence, Machine Learning, Precision Medicine, Integrated Health Care Systems, Medical Informatics

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Introduction

Machine learning, a popular subdiscipline of Artificial Intelligence, utilizes large datasets and identifies interaction patterns among variables. These techniques can discover previously unknown associations, generate novel hypotheses and drive researchers and resources towards most fruitful directions.¹ Machine learning can be applied in various fields, including financial, automatic driving, smart home, etc. In medicine, machine learning is widely used to build automated clinical decision systems.

Most machine learning approaches fall into two main categories: supervised and unsupervised methods. Supervised methods are great for classification and regression. Recent examples include: detection of a lung nodule from a chest x-ray;² risk estimation models of anticoagulation therapy;³ implantation of automated defibrillators in cardiomyopathy;⁴ use in classification of stroke and stroke mimic;⁵ modeling of CD4+ T cell heterogeneity;⁶ outcome prediction in infectious diseases;⁷ detection of arrhythmia in electrocardiogram;⁸ and design and development of *in silico* clinical trial⁹ among others.

Unsupervised learning does not require labeled data. It aims to identify hidden patterns present in the data and is often used in data exploration and novel hypotheses generation.² In three separate studies in heart failure with preserved ejection fraction among patients who had a heterogeneous condition with no proven therapies,¹⁰ researchers used unsupervised learning² to revisit failed clinical trial such as treatment with spironolactone,¹¹ enalapril,¹² and sildenafil¹³ versus placebo to identify a subclass of patients who might benefit from specific therapies, without human intervention.

There are other algorithms, such as reinforcement learning, which can be viewed as a combination of supervised and unsupervised learning to maximize the accuracy using trial and error.¹⁴ ([table 1](#)).

Table1.

Three main machine learning strategies, their characteristics, scope, and limitations

ML types	Algorithms Description	Characteristics	Limitation
Supervised Learning	Labeled dataset. System trained with human feedback	Applications include Classification, Regression, and Prediction; ideal for modeling disease prognosis or treatment outcome. Modeling algorithms include Artificial Neural Network (ANN), Support Vector Machine (SVM), Random Forest (RF)	Requires a large amount of labeled data for training; need validation in an independent cohort.
Unsupervised Learning	Non-labeled data by humans	Applications include mainly pattern recognition; ideal for modeling disease mechanisms, identifying hidden patterns in genotype or phenotype data. Modeling algorithms include various clustering methods	Needs validation in several independent cohorts
Reinforcement Learning	Hybrid approach; The goal is to maximize accuracy by trial and error; especially useful in a complex environment	Applications include chemistry, robotics, resource management in computer clusters, personalized recommendations	Memory intensive

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Deep learning is a subset of machine learning which mimics the operation of the human brain using multiple layers of artificial neuronal networks to generate automated predictions from training datasets. Models based on

deep learning strategy tend to have multiple parameters and layers; thus, model over-fitting could lead to poor predictive performance. Increasing the training sample size, decreasing the number of hidden layers, and ensuring the data is well-balanced can help prevent overfitting. Overall, deep learning is compelling in image recognition¹⁵ as well as in modeling disease onset¹⁶ using temporal relations among events. A deep neural network was trained on more than 37,000 head computed tomography scans for intracranial hemorrhage and subsequently evaluated on 9,500 unseen cases, reducing time to diagnosis of new outpatient intracranial hemorrhage by 96% with an accuracy of 84%.¹⁷

Cognitive computing as a subset of artificial intelligence involves self-learning systems using pattern recognition, and natural language processing for semi, or unstructured data. Cognitive computing mimics the operation of human thought processes, with the goal of creating automated computerized models that can solve problems without human assistance. Examples include research in computer-brain-interface,^{18,19} and commercial products such as the IBM Watson.²⁰

Although none of these approaches can rapidly and simultaneously consider different disease-related parameters in a user-independent fashion, they are promising venues and are changing the way medicine is practiced. Healthcare providers should be ready for the upcoming Artificial Intelligence age and embrace the added capabilities that would lead to more efficient and effective care. In this article, we review the applications and challenges as well as ethical consideration and perspectives of machine learning in medicine, translational research, and public health (table 2).

Table 2.

Selected areas in medicine where machine learning has high potentials and implications

Field	Application
Clinical	Disease prediction and diagnosis
	Treatment effectiveness and outcome prediction
Translation	Drug discovery and repurposing
	(<i>In Silico</i>) Clinical trial
Public health	Epidemic outbreak prediction
	Precision health

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Clinical Application

Disease prediction and diagnosis:

Despite the increasing application of artificial intelligence in healthcare, the research mainly concentrates around cancer, nervous system, and cardiovascular diseases, because they are the leading causes of disability and mortality. However, infectious and chronic diseases (e.g., type 2 diabetes,²¹ inflammatory bowel disease,²² *C. difficile* infection⁹) have also been getting considerable attention. Early diagnosis can now be achieved for many conditions by improving the extraction of clinical insight and feeding such insight into a well-trained and validated system.²³ For instance, the United States Food and Drug Administration (FDA) permitted applying of diagnosis software designed to detect wrist fractures in adult patients.²⁴ In another study on 1,634 images of cancerous and healthy lung tissue, the algorithm identified healthy cases and distinguished, as accurately as three pathologists, between two common types of lung cancer.²⁵ In the United States, more than 6% of adult populations are affected by depression. Predicting major depressive disorder was 74% accurate by image heatmap pattern recognition.²⁶

Several studies are looking at the potential of artificial intelligence in timely and precise disease diagnosis. Supervised methods are effective tools at capturing nonlinear relationships for complex and multifactorial disease classification. In a 260 patients cohort study, Abedi V. *et al*²⁷ found that the model can better diagnose acute cerebral ischemia than trained emergency medical respondents. Although noisy data and experimental limitations reduce the clinical utility of the models, deep learning methods can address these limitations by reducing the dimensionality of the data through layered auto-encoding analyses. Examples include: analysis of more than 1,400 images from 308 histopathology region of skin to detect basal cell carcinoma and differentiate malignant from benign lesions, achieving a diagnostic accuracy of >90% compared with experts;²⁸ or examination of more than 41,000 digital screening breast mammographic for identifying dense or non-dense breast tissue, where 94% of the 10,763 deep learning assessments were accepted by the interpreting radiologist.²⁹

Treatment effectiveness and outcome prediction:

Treatment effectiveness and outcome prediction are also important areas with the potential clinical implication in disease management strategies and personalized care plans. A decade ago only molecular and clinical information was exploited to predict cancer outcomes. With the development of high-throughput technologies, including genomic, proteomic, and imaging technologies, new types of input parameters have been collected and used for prediction. With a large sample size and integrated multi-modal data types, including histological or pathological assessments,³⁰ these methods could considerably (15–25%) improve the accuracy of cancer susceptibility, outcome prediction, and prognosis.³¹

Electronic health records (EHRs) are effective tools for documenting and sharing healthcare information. Integrating machine learning-based modeling designed specifically for administrative datasets can facilitate the detection of potential complications, improve health care resource utilization, and outcome at a personalized level.^{32,33} Utilization of machine learning applied to EHR data has been shown to predict outcome in sepsis patients. Large scale machine learning-based mortality study in more than 170,000 patients with 331,317 echocardiography by Manar Smad *et al.*³⁴ achieved 96% accuracy to predict patients survival based on echocardiography combined with EHR data. In terms of algorithm improvement Stephen W. Smith *et al.*³⁵ developed a deep neural network model for 12-lead ECG analysis compared to the conventional algorithm in emergency department ECGs, their result showed an accuracy of 92% for finding a major abnormality.

Artificial Intelligence analytics can be used in chronic disease management characterized by multi-organ involvement, acute variable events, and long illness progression latencies. For instance, retinopathy can be predicted using machine learning. Training two validation dataset using deep learning to detect and grade diabetic retinopathy and macular edema achieved a high specificity and sensitivity for detecting moderately severe retinopathy and macular edema after each image was graded by ophthalmologists between three and seven times.³⁶

To improve care in congestive heart failure, one study used supervised machine learning on 46 clinical variables from 397 patients with heart failure with preserved ejection fraction. Phenotypic heatmap predicted

patient survival more accurately than commonly employed risk assessment tools.²

One of the goals of precision medicine in cancer is the accurate prediction of optimal drug therapies from the genomic data of individual patient tumors.³⁷ In one study researchers present an open-access algorithm for the predictive response of cancers to seven common chemotherapeutic medications.³⁸ Precision medicine success depends on algorithm ability to translate large compendia of *-omics* data into clinically actionable predictions. For example, Costello J. C. *et al.*³⁹ analyzed 44 drug sensitivity prediction algorithms on 53 breast cancer cell lines with available genomic information to fulfill dose-response values of growth inhibition for each cell line exposed to 28 therapeutic compounds.

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[Translation Application](#)

Drug discovery and repurposing:

About 25% of all discovered drugs were the result of a chance when different domains were brought together accidentally.⁴⁰ Targeted drug discovery is preferred in pharmaceuticals due to the explicit mechanism, higher success rate, and lower cost when compared to traditional blind screening. Machine learning is now utilized in the drug discovery process due to the followings; 1) high costs of drug development; 2) increasing availability of three-dimensional structural information that can guide the characterization of drug targets, and 3) extremely low success rates in clinical trials.⁴¹ Machine learning can be used as a bridge to achieve cross-domain linkage. It can identify a newly approved drug by recognizing contextual clues like a discussion of its indication or side effects.²⁰

Despite these novel approaches in drug discovery, there are important challenges, including data access and the fact that in general, different data sets are stored in a variety of repositories. Furthermore, raw data from clinical trials and other pre-clinical studies are typically not available. However, overall, artificial intelligence has been successful when applied to available sources, including the use of drug information to extract insight about mechanism-of-action by applying techniques such as similarity metrics across all diseases to find shared pathways.²⁰ Another example includes the use of natural language

processing for identification of hidden or novel associations that might be important in the detection of potential drug adverse effects based on scientific publications.⁴²

Clinical trial and *in silico* clinical trials:

Clinical trial design has its roots in classical experimental design. However, the clinical investigators are not able to control various sources of variability. Ethical issues are paramount in clinical research. Subject enrollment can become lengthy and costly.^{43,44}

Machine learning approach using *in silico* dataset was introduced to describe the numerical methods used in drug development in oncology by modeling biological systems in the setting of clinical trial studies and hospital databases, paving the way to predictive, preventive, personalized and participatory medicine.⁴⁵ This approach gives the researchers the ability to partially replacing animals or humans in a clinical trial and generates virtual patients with specific characteristics to enhance the outcome of such studies. These methods are especially helpful for pediatric or orphan disease trials and can be applied in pharmacokinetics and pharmacodynamics from the preclinical phase to post-marketing.^{46, 46} In a study, a large *in silico* randomized, placebo-controlled Phase III clinical trial study was designed where investigators used virtual treatments on synthetic Crohn's disease patients. Results showed a positive correlation between the initial disease activity score and the drop in the disease activity score but with different medications efficacy.⁴⁷ The model did not highly score the investigational drug GED-0301; this prediction was further validated when the company which was running the clinical trial on GED-0301, has stopped the phase III trial after it failed to clear an interim futility review.⁴⁸ *In silico* clinical trials can have considerable potentials in design and discovery phases of biomedical product, biomarker identification, dosing optimization, or the duration of the proposed intervention.⁴⁹

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Public Health Relevance

Epidemic outbreak prediction:

The infectious disease distribution pattern between population groups with known probabilities are based on prior knowledge of ecological and

biological features of the environment. Early prediction of the epidemic (such as peak and duration of infection) is possible if model parameters are partially known.⁵⁰ Potential outbreak areas for filoviruses were predicted in West, Southwest and Central parts of Uganda which is related to bat distribution and previous outbreaks areas.⁵¹ In another study, Kesorn K. *et al.*⁵² predicted the morbidity rate of dengue hemorrhagic fever in central Thailand by estimating the infection rate in the female *Aedes aegypti* larvae mosquitoes and achieved a prediction accuracy of >95% and 88% in the training and test set, respectively.

Precision Health

Genetic and biomedical studies have continued investigation efforts with the goal of revealing connections between genes and human traits or diseases. Regularized logistic regression is an important tool for related applications. Many studies rely on large-scale sensitive genotype or phenotype data and sharing across institutions is paramount for the success of such studies.⁵³

There are many such examples in recent years. For instance, in a recent case-control study with limited sample size, researchers developed an algorithm to integrate personal whole genome sequencing and EHR data and used this algorithm to study abdominal aortic aneurysm. They assess the effectiveness of modifying personal lifestyles given personal genome baselines, demonstrating the model's utility as a personal health management model. Such studies have the potential to shed lights on the biological architecture of other complex diseases.⁵⁴ In a recent review, Torkamani *et al.*, examine the core disciplines that enable *high-definition medicine* given our recent technological advances and high-resolution data.⁵⁵

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Challenges and perspectives

Machine learning's ultimate goal is to develop algorithms that are capable of self-improving with experience and continuously learning from new data and insights, to find answers to an array of questions. The compelling opportunities in precision medicine offered by complex algorithms are accompanied by computational challenges. In 2012 the Obama administration announced "Big Data Research and Development Initiative" investment to "help solve some of the Nation's most pressing

challenges”.⁵⁶ The achievement of this potential requires novel approaches to address at least three technical challenges:⁵⁷ 1) *volume* – scale of data inputs, outputs, and attributes; this challenge can be addressed in part by using clusters of CPUs, data sharing system or cloud and deep learning methods; 2) *variety* – different formats of data (image, video, and text); this challenge can be partially addressed by using novel deep learning methods to integrated data from various sources; and, 3) *velocity* – speed of streaming data; to address this challenge, online learning approaches can be developed.

The ethical challenges presented by data science have also been an area of debate. These challenges can be mapped within the conceptual space and described by three branches of research: the ethics of data and privacy, the ethics and morality of algorithms, and the ethics and values of practices.⁵⁸ Among those, privacy has been the center of attention. Privacy is defined as a fundamental human right in the Universal Declaration of Human Rights at the 1948 United Nations General Assembly. Machine learning plays a key role in the development of precision medicine, whereby treatment is customized to the clinical or genetic risk factors of the patient. These advances require collecting and sharing the massive amount of data and thus generate concern about privacy.⁵⁹

At the same time, healthcare institutions need to communicate with the public and collaborate with scientific communities, as well as government agencies.⁶⁰ In this situation, a privacy-preserving framework is necessary and should be applied to a large range of domains where the privacy and confidentiality of study participants and institutions is of concern.⁶¹ As standard practice, many institutions collaborate and use the de-identification process to share clinical data; or perform a meta-analysis, and each contributing site performs analysis in-house. These processes reduce the scope of clinical data sharing. For example, the DNAnexus clinical trial solution service powers the FDA’s platform for advancing regulatory standards.⁶² St. Jude Cloud is a data-sharing resource for the global research community.⁶³ eMERGE is a national network organized and funded by the National Human Genome Research Institute (NHGRI) that combines DNA biorepositories with electronic medical record (EMR) systems for large-scale, high-throughput genetic research in support of implementing genomic medicine.⁶⁴ In Europe, the UK Biobank is a national and international health resource with unparalleled research opportunities, open to all *bona fide* health researchers.⁶⁵

The most important issue when developing machine learning in a clinical setting is the issue of trust when both clinicians and patients accept the recommendations provided by the system.⁶⁶ The data is noisy, complex, high-dimensional with thousands of variables, and biased for the catchment area of the originating hospital systems where the model was trained. Furthermore, missing data is not at random. Missingness can be due to incompleteness, inconsistency, or inaccuracy.^{67,68} Imputation, predicting missing values, also has its unique challenges. Standardized techniques such as the MICE algorithm⁶⁹ or novel imputation methods⁷⁰ have been proposed. Other challenges in mining the EHR data includes: 1) different protocols and changes are introduced at various time period, without documentation for the research team; and 2) policy changes and reimbursement rules are introduced that may affect how patients seek care and how the treatment is re-designed based on their needs and their insurance coverage. Therefore, to develop models using EHR, the researchers must work closely with care providers and others within the healthcare system to increase the predictive power of the modeling-enabled discoveries.

Other limitations are lack of interoperability across technology platforms over time and massive expansion of structured and unstructured data elements. Natural language processing can be used to process and contextualizes different medical words and expressions.⁷¹ However; robust infrastructures have to be in place to be able to handle a large number of clinical notes. For instance, it is possible to use robust infrastructure to process millions of notes and identify patients who are in need of a follow-up appointment for preventive care in hospital settings.⁷²

Today's machine learning approaches are near to real-world conditions. Due to the rapid technological advancements, tasks previously limited to humans will be taken on by algorithms.⁷³ Machine learning's ability to transform data into insight will affect the field of medicine, displacing much of the work of radiologists and anatomical pathologists. However, clinical medicine has always required doctors to handle huge

amounts of data, from history and physical exam to laboratory and imaging studies and, newly genetic data. The ability to manage this complexity has always set good doctors apart.⁷⁴

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Clinical Significance

Artificial intelligence increases learning capacity and provides decision support system at scales that are transforming the future of healthcare.

Artificial intelligence has been implemented in disease diagnosis and prognosis, treatment optimization and outcome prediction, drug development and public health.

Technological advances require collecting and sharing the massive amount of data and thus generate concern about privacy.

[Artificial Intelligence Transforms the Future of Healthcare - PMC \(nih.gov\)](#)

Study4

In 2020, the U.S. Department of Defense officially disclosed a set of ethical principles to guide the use of Artificial Intelligence (AI) technologies on future battlefields. Despite stark differences, there are core similarities between the military and medical service. Warriors on battlefields often face life-altering circumstances that require quick decision-making. Medical providers experience similar challenges in a rapidly changing healthcare environment, such as in the emergency department or during surgery treating a life-threatening condition. Generative AI, an emerging technology designed to efficiently generate valuable information, holds great promise. As computing power becomes more accessible and the abundance of health data, such as electronic

health records, electrocardiograms, and medical images, increases, it is inevitable that healthcare will be revolutionized by this technology. Recently, generative AI has garnered a lot of attention in the medical research community, leading to debates about its application in the healthcare sector, mainly due to concerns about transparency and related issues. Meanwhile, questions around the potential exacerbation of health disparities due to modeling biases have raised notable ethical concerns regarding the use of this technology in healthcare. However, the ethical principles for generative AI in healthcare have been understudied. As a result, there are no clear solutions to address ethical concerns, and decision-makers often neglect to consider the significance of ethical principles before implementing generative AI in clinical practice. In an attempt to address these issues, we explore ethical principles from the military perspective and propose the “GREAT PLEA” ethical principles, namely Governability, Reliability, Equity, Accountability, Traceability, Privacy, Lawfulness, Empathy, and Autonomy for generative AI in healthcare. Furthermore, we introduce a framework for adopting and expanding these ethical principles in a practical way that has been useful in the military and can be applied to healthcare for generative AI, based on contrasting their ethical concerns and risks. Ultimately, we aim to proactively address the ethical dilemmas and challenges posed by the integration of generative AI into healthcare practice

Study 5

Artificial intelligence in medicine: A comprehensive survey of medical doctor's perspectives in Portugal

Pedro, Ana Rita; Dias, Michelle B; Laranjo, Liliana; Cunha, Ana Soraia; Cordeiro, João V. **PLoS One; San Francisco** المجلد ١٨, الإصدار ٩ (Sep 2023): e0290613. DOI:10.1371/journal.pone.0290613

Artificial Intelligence (AI) is increasingly influential across various sectors, including healthcare, with the potential to revolutionize clinical practice. However, risks associated with AI adoption in medicine have also been identified. Despite the general understanding that AI will impact healthcare, studies that assess the perceptions of medical doctors about AI use in medicine are still scarce. We set out to survey the medical doctors licensed to practice medicine in Portugal about the impact, advantages, and disadvantages of AI adoption in clinical practice. We designed an observational, descriptive, cross-sectional study with a quantitative approach and developed an online survey which addressed the following aspects: impact on healthcare quality of the extraction and processing of health data via AI; delegation of clinical procedures on AI tools; perception of the impact of AI in clinical practice; perceived advantages of using AI in clinical practice; perceived disadvantages of using AI in clinical practice and predisposition to adopt AI in professional activity. Our sample was also subject to demographic, professional and digital use and proficiency characterization. We obtained 1013 valid, fully answered questionnaires (sample representativeness of 99%, confidence level ($p < 0.01$), for the total universe of medical doctors licensed to practice in Portugal). Our results

reveal that, in general terms, the medical community surveyed is optimistic about AI use in medicine and are predisposed to adopt it while still aware of some disadvantages and challenges to AI use in healthcare. Most medical doctors surveyed are also convinced that AI should be part of medical formation. These findings contribute to facilitating the professional integration of AI in medical practice in Portugal, aiding the seamless integration of AI into clinical workflows by leveraging its perceived strengths according to healthcare professionals. This study identifies challenges such as gaps in medical curricula, which hinder the adoption of AI applications due to inadequate digital health training. Due to high professional integration in the healthcare sector, particularly within the European Union, our results are also relevant for other jurisdictions and across diverse healthcare systems.

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