Chapter

Unlocking the Potential of Artificial Intelligence (AI) for Healthcare

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Abstract

This book chapter examines the potential of artificial intelligence (AI) to improve healthcare. AI has become increasingly prominent in healthcare, providing the capability to automate tasks, analyze large patient data sets, and deliver quicker and more cost-effective healthcare. We focus on its various applications in healthcare including vital sign monitoring, glycemic control, radiology, and emergency room triage with point of care ultrasound (POCUS). We also address Ai's ethical, legal, and privacy implications in healthcare such as data protection and safeguarding patient privacy. Finally, we explore the potential of AI in healthcare improvement in the future and investigate the current trends, opportunities, and evolving threats posed by AI in healthcare, as well as its implications for human-AI interfacing and job security. This book chapter provides an essential and comprehensive overview of the potential of AI in healthcare, providing a valuable resource for healthcare professionals and researchers in the field.

Keywords: artificial intelligence (AI), healthcare clinical management, AI in healthcare, vital sign monitoring, glycemic control, radiology, point of care ultrasound (POCUS), ER triage, AI data security, human-AI interfacing, machine learning (ML), neural networks (NNs), deep learning (DL), AI ethical concerns, AI healthcare benefits

1. Introduction

AI has been rapidly increasing in popularity and application within the healthcare industry over the past decade. AI has the potential to greatly increase the efficiency and accuracy of healthcare, resulting in improved patient care, better decision-making, and overall cost savings. AI allows for complex and rapidly growing datasets to be evaluated and analyzed with unprecedented accuracy and detail, using machine learning (ML), neural networks (NNs), deep learning (DL), and large language models (LLM).

AI and ML are two distinct but related branches of computer science. The two are related in that AI requires data to be used in order to make decisions, and ML provides the tools to do so. Artificial intelligence is a spectrum of intelligence, learning, and analytical proficiency. Machine learning and deep learning are related applications within the artificial intelligence space with varying aptitudes and capabilities (see **Figure 1**). Machine learning (ML) can understand relationships from the data without the need to define them a priori and can derive predictive models without a need for strong assumptions about the underlying mechanisms. In other words, ML converts the inputs of an algorithm into outputs, using statistical tools [1, 2]. It can change when exposed to new data and can improve from experience.

In contrast, deep learning (DL) uses multilayered neural networks to compute large volumes of data and accept multiple data types (heterogenicity). This feature has proven applicability in healthcare, that is. the EHR system. Of the deep learning algorithm, convolutional neural networks (CNN) processes data exhibiting natural spatial invariance (clinical images) [1]. Compared to ML, DL requires considerably less human guidance, and the overall difference is how DL interprets and presents raw data.

The level of analysis, sophistication, and detail exhibited by AI would be impossible for humans to do alone. This can help healthcare organizations to gain insights and identify trends that would otherwise be difficult to detect. In addition, AI can provide real-time recommendations and feedback to healthcare professionals, helping them make better, more informed decisions.

As AI technology advances and becomes more integrated into healthcare systems, healthcare organizations can leverage its many advantages to become more efficient and effective such as automating mundane and repetitive tasks freeing up healthcare professionals to concentrate on more critical aspects of patient care. AI can also improve the accuracy and timeliness of diagnosis and treatment decisions, reducing the risk of medical errors, and potentially saving lives. Additionally, AI can be used to monitor patient health, alert healthcare professionals to potential issues before they become serious, predict future health outcomes, and help healthcare organizations

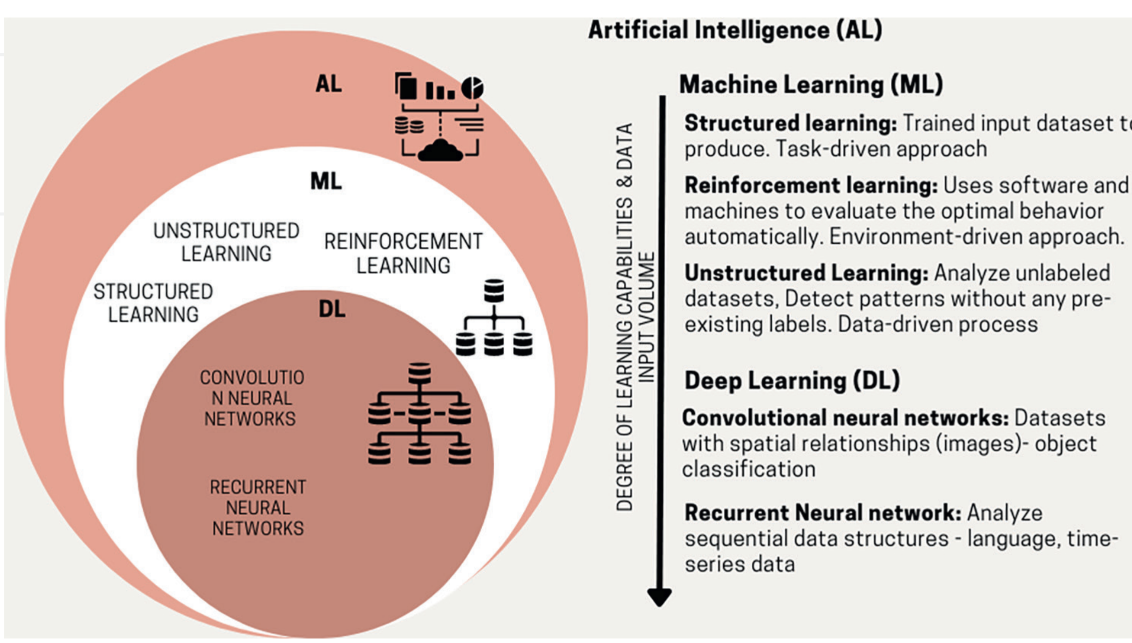

Figure 1.
Artificial intelligence (AI) hierarchical relationship.

better plan for potential scenarios. The recent arrival of conversational AI systems based on LLM such as ChatGPT has opened a plethora of potential uses including but not limited to preauthorization, automatic generation of medical reports, summarizing the electronic health record, and interactive computer-aided diagnosis (CAD) [3]. These applications are possible because LLM is efficient in a wide variety of tasks including summarization, machine translation, and quickly answering questions. Ultimately, AI applications enhance communication between healthcare professionals and patients, providing more personalized care and optimizing processes such as appointment scheduling and prescription refills. However, studies need to be performed and validated to confirm whether utilizing these resources brings ultimate value to patient care. See **Table 1** for acronyms and abbreviations.

2. Methodology

We conducted a literature search of articles on AI in various healthcare fields in English over the last five years on search engines: PubMed and Google scholar. The

Acronyms and abbreviations	Meaning
AI	Artificial intelligence
AI-ML	Artificial intelligence-machine learning
AUC	Area under the receiver operating characteristic (ROC) curve
CAD/CADe	Computer-aided diagnosis
CGM/rtCGM	Continuous glucose monitors/real-time CGM
CNN	Convolutional neural networks
CT	computed tomography scan
CXR	Chest X-ray
DL	Deep learning
DNN	Deep neural network
ER/ED	Emergency room/department
ESI	Emergency severity index score
IVC	Inferior vena cava
LLM	Large language models
MEWS	Modified early warning score
MI	Myocardial infarction
ML	Machine learning
MRI	Magnetic resonance imaging scan
NNs	Neural networks
POCUS	Point of care ultrasound
SIRS	Systemic inflammatory response syndrome
SOFA/qSOFA	Sequential organ failure assessment score/Q = quick

Table 1.
Acronyms and abbreviations.

following key terms were used to generate the search: "artificial intelligence (AI)" in healthcare, vital sign monitoring, glycemic control, radiology, point of care ultrasound (POCUS), ER triage, AI data security, human-AI interfacing, machine learning (ML), neural networks (NNs), deep learning (DL), AI ethical concerns, and AI healthcare benefits. For the first review, two team members manually went over articles. For the next step, various topics of artificial intelligence on different subjects, such as radiology, vital signs monitoring, glycemic control, point of care ultrasound, and ER triage, were divided among the authors with relevant specialties. Each author then wrote the section with following themes: its utility, challenges, liabilities, implications on job security, and future education.

3. Utility of AI in radiology

AI is increasingly being used in radiology to improve diagnostic accuracy, efficiency, and decision-making. Some of the most common applications of AI in radiology include image analysis, computer-aided diagnosis (CADe), image segmentation, automated image interpretation, and automated reporting [4–6].

AI-based systems can be trained to detect and identify specific structures or abnormalities on medical images such as tumors, blood vessels, or organ abnormalities [5, 7, 8]. This can improve diagnostic accuracy and efficiency by highlighting potential abnormalities that may have been missed by radiologists [9]. Additionally, AI-based systems can be used to assist radiologists in the diagnostic process by classifying different types of tumors or identifying specific patterns on medical images, which can help radiologists make more accurate, specific diagnoses, and guide treatment decisions [4, 5, 8]. AI-based systems can also be used to generate automated reports and summaries that include relevant information and analysis, which can save time, reduce the workload and errors caused by manual reporting, and improve communication with other healthcare providers [4, 6, 10].

AI applications have the protentional to be used in radiology for detection and characterization in many body systems [8, 9]. Recent advances in AI for thoracic applications have focused on using deep learning techniques to assist with a lung cancer diagnosis and pulmonary nodule detection on CT scans. In abdominal and pelvic applications, AI has been used to assist with liver lesion analysis and the detection of abnormalities on CT and MRI scans. General lesion analysis using AI typically involves training a model on a large dataset of images to identify and classify various types of lesions [11]. This can include detecting and characterizing tumors, identifying and measuring anatomic structures, and determining the presence of certain disease states.

3.1 How is AI utilized in radiology?

AI in radiology utilizes the expertise of experienced radiologists to supply predefined criteria for properly programming the algorithm [4, 8]. Radiologists with specialized knowledge in chest, abdominal, or musculoskeletal radiology can offer the essential insight and direction required to train AI algorithms to identify and locate specific structures or anomalies on medical images. This involves providing the algorithm with a set of "ground truth" or baseline images that have been annotated by radiologists to indicate the presence and location of specific structures or abnormalities. The algorithm can then learn to identify these structures or abnormalities based on the patterns and features that are present in the images.

AI algorithms can also learn from a large volume of data with supervised or unsupervised strategies. Supervised learning is when the algorithm is provided with labeled data, where each image is associated with a specific diagnosis or label [4, 12]. This allows the algorithm to learn from the data and make predictions about new images. Unsupervised learning is when the algorithm is provided with unlabeled data, where the algorithm must learn to identify patterns and features in the data without any prior knowledge [4, 12]. This can be useful for identifying new or previously unknown patterns or features in the data. The algorithm can also be trained to extract information *via* patterns and share deep insights that can be used to improve diagnostic accuracy, efficiency, and decision-making [4].

3.2 How can AI transform the work of a radiologist?

AI can play a transformative role to help unlock the solutions to many challenges of radiology such as increasing workload and staff shortages. AI can also transform the work of a radiologist by mainly following steps in image analysis, which includes detection, characterization, and monitoring in several ways [5, 11, 13] (see **Figure 2**). One of the most important areas where AI is used in radiology is **image analysis,** where AI-based systems can be trained to detect and identify specific structures or abnormalities on medical images such as tumors, blood vessels, or organ abnormalities. This can improve diagnostic accuracy and productivity by highlighting potential abnormalities that may have been missed by the human eye [5, 11].

Another important area is **characterization,** where AI-based systems can be trained to classify and characterize different types of abnormalities or lesions [5, 11]. For example, AI algorithms can be used to differentiate benign from malignant tumors or to classify different types of liver lesions. This can help radiologists to make more accurate and specific diagnoses and guide treatment decisions [5, 8]. This can also reduce the need for additional imaging or biopsies, which can save time and money.

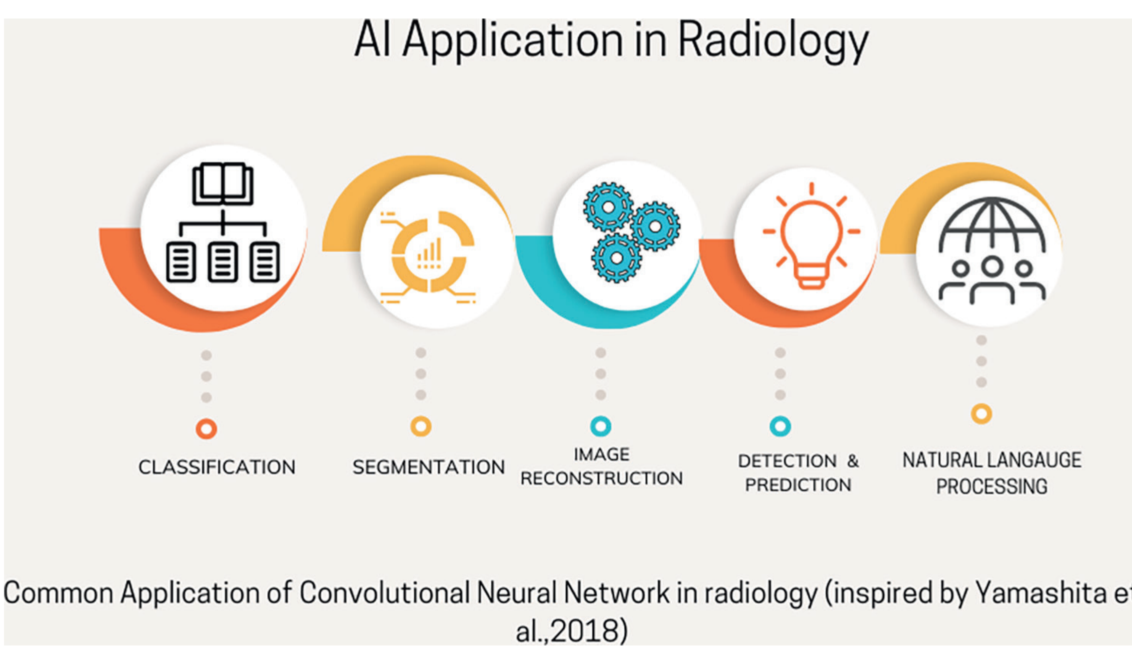

Figure 2.
AI applications in radiology.

Monitoring is another area where AI is being used in radiology, where AI-based systems can be used to monitor changes in lesions over time [5]. For example, AI-based systems can track the growth of a tumor or the response to treatment [11], which can help radiologists to make more informed decisions about patient care. This can also help to identify patients who need additional monitoring or treatment and can lead to improved patient outcomes.

AI is also being used in **image acquisition** by deep learning-based reconstruction algorithms that can reduce scan time and improve image quality, especially in MR imaging. MR imaging can take anywhere from 30 and 60 minutes and occasionally longer depending on the protocol. Some patients, particularly elderly patients, can become uncomfortable and claustrophobic lying in a confined space for this period of time. Being able to obtain high-quality imaging in a shorter time can help alleviate this issue and reduce the presence of motion artifact. This can ultimately improve the diagnostic confidence in the images and prevent unnecessary repeating sequences [14].

Additionally, AI can assist radiologists by providing them with **automated reports and summaries** that include relevant information and analysis, which can save time, reduce the workload and errors caused by manual reporting, and improve communication with other healthcare providers [8]. AI can also support radiologists by integrating with other healthcare systems, providing them with comprehensive patient information and data from other sources such as electronic health records, lab results, and previous imaging studies, which can provide a more comprehensive view of the patient's condition and assist in the diagnostic process.

It is important to note that AI in radiology still requires human interpretation and oversight, as AI algorithms are not perfect, they can make errors or miss certain findings. It is anticipated that AI in radiology will become increasingly more precise and reliable over time as more data is acquired and technology advances.

3.3 Challenges of AI and liabilities around wrong and missed diagnosis

Though AI has the promise to improve diagnostic accuracy and efficiency, it also poses certain liabilities related to wrong and missed diagnoses [9]. One potential liability is that AI systems may produce incorrect or unreliable results due to factors such as poor image quality, incorrect data input, or errors in the algorithms used to analyze the images [15]. This could lead to wrong, delayed, or missed diagnoses, or unnecessary treatments [9].

Another potential liability is that AI systems may not be able to detect certain types of lesions or diseases, particularly those that are rare or atypical. Additionally, there are concerns about the lack of standardized benchmarks to compare and validate AI models for practical implementation. This could lead to missed diagnoses, which can be particularly dangerous if the condition is serious or life-threatening.

AI systems also require proper validation and testing before they are used in clinical practice. Validating data sets is time-consuming, and thus can jam many machine-learning projects. Handling unexpected inputs such as artifacts and poor imaging can also pose a problem in high-quality data sets. Medical research on data sets can also act as a hurdle as many patients value their privacy [16, 17]. If they are not appropriately validated, they may not be suitable for the intended use or population, and this can lead to wrong or missed diagnoses as well.

Additionally, there is also a lack of reasoning and an inability to explain AI models [17]. There is the potential that AI systems could be used to override the judgment of

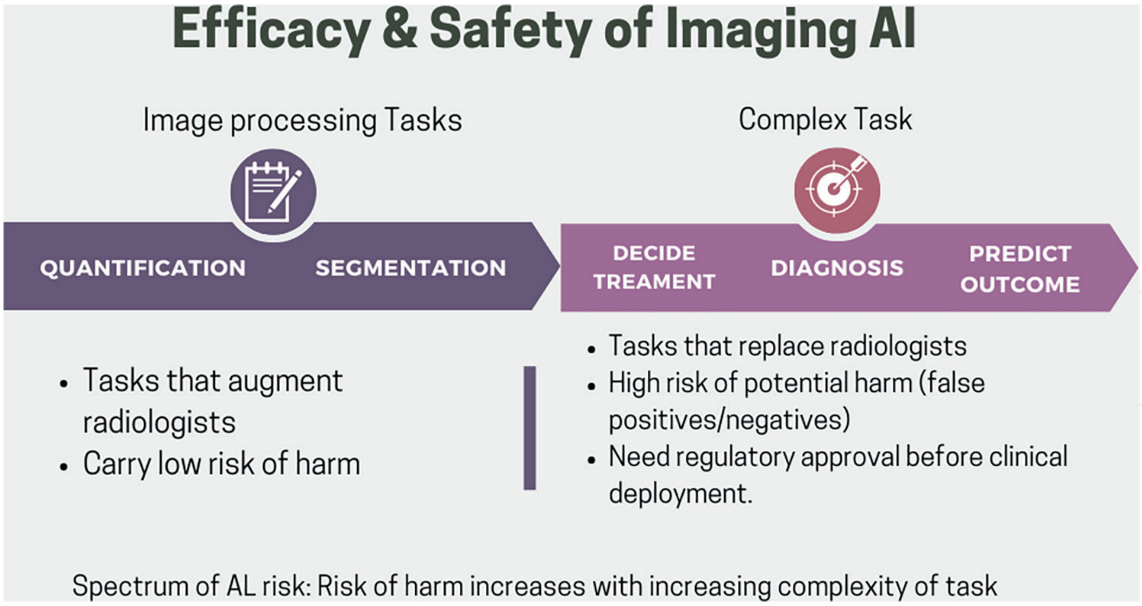

Figure 3.
Efficacy and safety of images.

radiologists, leading to an increased risk of wrong or missed diagnoses if the radiologist's judgment is ignored (see **Figure 3**).

To mitigate these liabilities, it is imperative to ensure that AI systems are properly validated and tested before they are used in clinical practice and that radiologists are properly trained in their use. Since investigating liability issues will require different skills from lawyers and additional evidence from technology along with medical expert opinion, we will need support from our technology law colleagues to design regulations [18]. It is vital to have proper governance, policies, and regulations in place for the use of AI in radiology.

3.4 Future implications for job security

AI has the potential to construct intelligent applications that can mimic the cognitive capabilities of humans, potentially revolutionizing the workforce in myriad ways. Some experts believe that AI could eventually replace certain tasks currently performed by radiologists and technologists [17] such as the interpretation of medical images. However, it is also possible that AI could augment radiologists' abilities and productivity, allowing them to spend more time on higher-level tasks such as consulting with other physicians, analyzing more complex cases, and providing follow-up to patients [19]. Though there are more than 80 approved algorithms in the US and Europe, only 40 of these have been approved by the FDA and only 34% of those were used for interpretation. The number of radiologists working in the US has risen by 7% in five years from 2015 to 2019 [20, 21].

Regarding job security, it is likely that radiologists and technologists who are trained and experienced in using AI systems will be in high demand. However, those who are not able or refuse to adapt to this new technology may face challenges in their job market [7, 10, 17]. Administrative staff may also be impacted as AI can automate some of the tasks they do, but this may also be a positive change as it can lead to more time for the staff to focus on patient care and other important tasks.

Overall, the effects of AI on the radiology workforce will depend on how the technology is adopted and implemented. Radiologists, standing at the leading edge of digital medicine, can provide support in the incorporation of AI into healthcare, their role in diagnostics communication, the incorporation of patient values and preferences, medical judgment, quality assurance, education, policy-making, and interventional procedures and ensures that they cannot be replaced by AI [22]. However, it is important for all radiologists, technologists, and administrative staff to stay informed about the latest developments in AI and work to develop the necessary skills to remain competitive in the field [23].

3.5 Future resident education

The increasing presence of AI applications in radiology necessitates educators to prepare trainees and radiologists as proficient users and stewards of AI technology. Yet, despite the controversy around if and to what extent AI should be incorporated into radiology residency programs, organized AI education and AI-ML curricula are still limited to a few institutions, with formal training opportunities lacking across the board.

AI has the potential to revolutionize radiology resident education by providing new tools and resources for teaching and learning and is likely to include a greater emphasis on AI-ML curricula and precision medical education [24, 25]. By incorporating AI and machine learning into radiology resident education, they can stay up to date with the latest techniques and technologies used to diagnose and treat patients and gain valuable experience with AI as it becomes increasingly important in healthcare.

One potential application of AI in radiology resident education is the use of AI-assisted image interpretation, which could help residents to develop their diagnostic skills and improve their understanding of complex medical images [25]. For example, AI systems can be used to identify and highlight certain features on an image such as tumors or blood vessels, which can help residents to identify these structures and improve their diagnostic accuracy more easily.

Another potential application of AI in radiology resident education is the use of virtual reality and simulation to provide hands-on training experiences [26, 27]. This technology can be used to create realistic simulations of medical scenarios such as a surgical procedure or an interventional radiology procedure, which can provide residents with an immersive and interactive learning experience.

AI can also be used to provide personalized and adaptive learning experiences to analyze each resident's progress and create personalized learning plans [24, 25]. For example, AI-based systems can be used to track residents' progress, provide feedback, and adjust the learning experience based on their strengths and weaknesses. This can include providing tailored feedback and resources to help them improve their diagnostic accuracy, as well as providing opportunities for hands-on training and simulation. By incorporating AI-ML curricula for radiology residents, the residency program can be at the forefront and focus on teaching residents the fundamental concepts and techniques of AI and machine learning such as data pre-processing, coding, model training, theory, and evaluation [28]. This would enable residents to understand how AI systems work and how to use them effectively in their practice. Precision medical education, which is an approach that aims to provide tailored education based on individual needs and characteristics, will also play an important role in and would involve using AI systems to personalize the learning experience for each resident, considering their strengths, weaknesses, and learning style [24, 28].

Additionally, AI can also be used for automated grading and feedback for radiology residents, which can save time for educators and provide more accurate and consistent feedback to the residents. Overall, the future of AI in radiology resident education will be closely tied to the development of AI-ML curricula and precision medical education encompassing the three learning theories (behaviorist, cognitive, and constructivist), which will enable residents to learn the latest techniques and technologies in an effective and efficient way and personalize the learning experience based on the residents' needs [24].

A recently developed elective in data science pathway (DSP) for fourth-year radiology residents at Brigham and Women's Hospital (BWH) in Boston has the potential to prepare the next generation of radiologists to lead the way in artificial intelligence and machine learning (AI-ML) [28]. The resident feedback from the pilot resulted in the establishment of a formal AI-ML curriculum for future residents, which included logistical, planning, and curricular considerations for DSP implementation at other institutions [28].

In summary, AI has the potential to greatly enhance radiology resident education by providing new tools and resources for teaching and learning, improving diagnostic skills, providing hands-on training experiences, and personalized learning experiences, as well as automated grading and feedback.

AI will impact radiology such asmany other medical fields, but radiologists can play a leading role in this forthcoming change by reducing the huge amount of data and information into the most relevant information.

4. AI and ML in emergency room triage and point of care ultrasound

Artificial intelligence in medical practice is shaping the way clinicians assess, analyze, and diagnose potentially life-threatening conditions, which will significantly impact the delivery of emergency care. The use of AI algorithmic systems may give the tools to possibly overcome previously ingrained limitations in care delivery strategies [29] thus extending the ability of emergency physicians to diagnose and treat acute and critical illnesses. Over the last 10 years, the U.S. Food Drug and Administration (FDA) has approved more than 500 AI and ML devices [30]. Of these, 100+ were radiology applications for devices used during an emergency.

This section will highlight the applications of artificial intelligence (AI), machine learning (ML), deep learning (DL), and convolutional neural networks (CNN) in emergency room triage and their use, specifically in point of care ultrasound testing. The applicability of these technologies has an obvious advantage in emergency medicine as every year the demands on the emergency medicine practitioner increase as the number of emergency room visits grows and physicians are expected to care for more patients with fewer resources. The ability to provide timely efficient and accurate life-saving interventions is crucial, and AI holds the potential to help physicians streamline processes, increase efficiency, and cognitively offload.

4.1 AI impact on emergency room care

Triage is the prioritization of the sick and injured based on their need for emergency treatment. Traditionally, in the emergency department clinical support staff gather primary patient demographic data, vital signs, and basic information about a patient's initial presenting problem. The patient then undergoes a brief evaluation by a clinician, usually a nurse, to determine the patient's acuity or need for emergent care or resources. Commonly during this process, a patient is assigned an emergency severity index (ESI) score, which is a common triage tool that provides a clinically relevant framework to stratify patients into five groups from one (most urgent) to five (least urgent) based on acuity and resource needs. This system essentially determines who receives care first. Subsequently, clinicians thoroughly assess presenting symptoms, perform appropriate physical examinations, order applicable laboratory studies, imaging studies, and consultations and either discharge the patient to home or admit them to the hospital as indicated [31]. With the growing number of emergency room visits annually and a growing shortage of nurses and emergency medicine practitioners, the ability to provide timely efficient and accurate life-saving interventions is crucial.

Effective triage is of the utmost importance to patient quality of care and outcome, especially as ER capacities are further and further stretched by increased volume and decreased resources, which have led to prolonged ED stays and wait time for care. Although ER wait times are multifactorial, convenient registration and the early identification of impending life-threatening conditions can obviate adverse patient outcomes and decrease mortality. One study that assessed the performance of a deep learning system, PatientFlowNet, in predicting patient flow in emergency departments found that the PatientFlowNet model prediction of patient arrival rates was higher, with substantially more accuracy in predicting treatment and discharge rates than the baseline methods used in the ER. The resulting mean absolute error was 4.8% lower than the leading baseline [32]. Applying AI tools that combine both clinical narratives (symptoms, pain scores, and ESI) and structured data (demographics and vitals), there is potential to positively influence outcomes.

The AI algorithmic tool (TriageGO) recently developed at Johns Hopkins aims to integrate patient medical health records with presenting symptoms, as well as vital signs to further risk stratify patients and predict morbidity and mortality [33]. Additionally, the DNN model with word embedding AI tool, which integrated clinical narratives and structured data, outperformed and better predicts patients' hospitalization and discharge when compared to the rapid emergency medicine score (REMS) [34]. Furthermore, rapid response is paramount with time-sensitive complaints such as chest pains. Goto et al. neural networks AI model predicts whether patients presenting to ER chest discomfort needs urgent revascularization 12-lead EKG. Their AI model detects the presence of specific EKG characteristics not recognized by physicians [35]. Than et al. developed their "MI3 clinical support tool" to predict the likelihood of myocardial infarction (MI) using machine learning which achieved a high AUC (0.963) for diagnosing MI, which outperformed the European Society of Cardiology 0/3-hour pathway [36]. In all these examples, the impact of AI on today's healthcare system has the potential to be transformational.

4.2 AI impact on point of care ultrasound

Over the last twenty years, ultrasound equipment has become more effective, economical, and compact because of this the applications and uses have broadened and the use of ultrasound at the bedside as a modality has become more ubiquitous. This is especially palpable in the world of emergency medicine (EM). In EM, there is an inherent need to arrive at a time-sensitive diagnosis and initiate potentially life-saving treatments, and the use of bedside ultrasound of point of care ultrasound is a crucial tool that facilitates this. POCUS is the medical use of ultrasound (US) technology for the bedside evaluation of acute or critical medical conditions. It is utilized for diagnosis, the guidance of procedures, monitoring of certain pathologic states, and as an adjunct to therapy. It has also demonstrated its utility as an adjunct in the resuscitation of the critically ill.

POCUS examinations are typically performed, interpreted, and integrated into care by the treating physician in real-time at the bedside making it distinct from traditional radiology-based applications [37]. Instead of performing a systems-based study designed to interrogate a particular anatomic area, POCUS seeks to help answer specific clinical questions that are often binary in nature (e.g. is there free fluid in the peritoneum, is there a pneumothorax, is there hydronephrosis, etc.). An additional factor that differentiates POCUS from the traditional use of medical ultrasound is the fact that POCUS practitioners are inherently diverse in their training and their ability. Ultrasound image acquisition is a user-dependent skill, and both because of this as well as the binary nature that drives POCUS use at the bedside, POCUS is an area that is ripe for the application of artificial intelligence (AI) and deep learning (DL) [37].

The use of DL in POCUS is varied as the model used depends on the problem it is trained to solve [37]. For example, DL in POCUS has been already used to help identify structures [37], for image enhancement [38], and for the classification of images [38]. In each different application, depending on the clinical question, the POCUS operator would "only need to provide an image, and the trained DL model would be able to immediately return the desired output, whether it be the outline of an organ, an enhanced US image, or the classification of the US image along with a confidence score [37]." The ability of DL application allows the practitioner to cognitively offload some elements of image acquisition and interpretation, and thus be able to concentrate more on real-time application and direct patient care [37]. The advantage of this is especially palpable in the world of emergency medicine (EM). In EM, there is an inherent need to arrive at a time-sensitive diagnosis and initiate potentially life-saving treatments.

AI and DL have demonstrated utility in several cardiac studies (e.g., estimation of ejection fraction, calculation of IVC caliber and collapsibility to predict fluid responsiveness, and the identification of cardiac tamponade), as well as pulmonary applications (AI-enhanced lung ultrasound in discriminating viral and bacterial pneumonia, estimation of size of pneumothorax based on location of lung point, and prediction of antibiotic response from US lung images using DL). These applications expand the EM practitioner's ability to risk stratify and implement treatment.

There is further potential, as AI ability evolves, to eventually achieve "real-time" image interpretation. This could in theory expand the number of POCUS practitioners beyond the ranks of physicians or EM-trained clinicians to first responders, EMTs, and those responding to mass-casualty events or real-time disasters. The ability to use POCUS in the "field" by untrained or novice user will allow those on site to potentially diagnose fractures, abdominal/thoracic free-fluid or hemorrhage, pneumothorax, or even cardiac standstill thus optimizing the triage response and subsequent allocation of resources. A similar conclusion can be drawn from those practicing in the global health realm, which is traditionally a lower-resource practice environment.

However, despite the obvious advantages, there are some limitations to the use of AI in POCUS. Imaging modalities, such as CXR, CT, and MRI, have standardized imaging protocols that are archived for later use/review leading to the construction of large persistent imaging datasets for AI to "mine." POCUS images and videos, on the other hand, are acquired and interpreted at the bedside, and findings are immediately applied with variable storage/archiving protocols depending on time limitations, patient acuity, machine capabilities, and institutional guidelines. Additionally, the large variation in POCUS user skill level, the order in which images are acquired, and the image acquisition technique create a great deal of "noise" or randomness which further complicates the building of large, standardized ultrasound datasets. Despite, this as AI advances and DL modeling and the creation of CNN becomes more sophisticated pathways are being found to navigate these limitations.

The impact of AI on today's emergency room can be transformational from its effects on triage to disease diagnosis and detection. AI can reintegrate and augment ER staff rather than replace the human workforce by decreasing the work burden and improving clinical outcomes.

5. AI and ML for vital sign monitoring

Today's healthcare, especially in the hospital setting, is complex, fast-paced, and busier than ever. Physicians make many individual decisions and treatment plans that are influenced by copious amounts of data that are collected and available for review in the EHR. Hospitalized patients are monitored frequently through vital signs and lab tests for signs of deterioration or instability. There is now a desperate need to automate this essential job and quickly alert clinicians if there are any signs of deterioration.

With the advancement of technology, artificial intelligence (AI) and machine learning (ML) algorithms are being used to analyze vital sign data and detect signs of disease in real-time, improving the accuracy and speed of diagnosis [39]. Conditions, such as sepsis, are commonly managed in the hospital setting and are the leading cause of inhospital death [40]. Traditionally, clinicians have relied on scoring systems such as the modified early warning score (MEWS), SIRS, Rothman index, sequential organ failure assessment score (SOFA), and quick SOFA (qSOFA) to identify patients at risk of deterioration. These scores utilize several data points from the patient's record to predict the risk of deterioration. However, due to their high sensitivity and low discriminatory ability, these scores may identify a larger number of patients at risk than present [39, 41].

Studies have concluded that individual machine learning models can predict sepsis onset ahead of time and with more accuracy compared directly with the traditional sepsis screening tools such as SIRS, MEWS, and SOFA scores [39, 41]. From a clinical perspective, ML models are particularly useful as they could trigger earlier detection of sepsis and allow for early antibiotic administration leading to decreased mortality. Some additional studies have also highlighted earlier predictions of severe deterioration in sepsis utilizing only vital signs. For instance, Mao et al. developed a gradient tree boosting model using data from only six vital signs: systolic BP, diastolic BP, heart rate, respiratory rate, peripheral capillary oxygen saturation, and temperature. This model was able to predict sepsis at the onset with high AUC (0.92) and septic shock 4 hours in advance with a high AUC (0.96). The model was also able to predict severe sepsis 4 hours in advance with a higher AUC (0.85) than the onset time for statistically calculated SIRS AUC (0.75) [42].

Additionally, AI-based monitoring incorporated into the EHR can facilitate the use of large volumes of data for the prediction of mortality in hospitalized patients. Shickel et al. used a modified recurrent neural network model on temporal intensive care unit data to develop DeepSOFA, a real-time mortality risk prediction score based on the traditional SOFA score [43]. This model compared the traditional SOFA scores to deep learning technology in augmenting a clinician's decision-making by generating accurate real-time prognostic data relating to mortality [43]. The DeepSOFA model was more accurate than baseline SOFA models for predicting inhospital mortality among ICU patients with baseline SOFA models significantly underestimating the probability of death, especially among non-survivors [43]. Recognition of mortality risk earlier in the disease course has the potential of aiding clinicians in taking preventative measures earlier and with more accuracy resulting in improved outcomes.

The COVID-19 pandemic demonstrated the utility of AI and ML for prehospital and posthospital management of patients. For instance, remote patient monitoring (RPM) came to the forefront during the pandemic as hospital systems became overwhelmed with patients. RPM is a healthcare technology that uses digital devices, wearable sensors, and wireless communication to collect and transmit medical data from patients outside of traditional clinical settings. Traditionally, RPM has been utilized to monitor chronic diseases; however, the pandemic accelerated the use of this technology for acute monitoring and management of patients with COVID-19 infections. RPM is achieved through use of smart devices such as blood pressure meters, thermometers, glucometers, and pulse oximeters utilizing an ecosystem known as the internet of health things (IoHT). IoHT refers to the interconnectivity of medical devices, wearables, and healthcare systems that allow for the exchange of health-related data between patients and healthcare providers.

ML techniques applied to enormous data sets generated through continuous monitoring of cardiac- and respiratory-related signals, coughing, body temperature, and patterns of activity collected from COVID-19 patients help predict the health status of a patient or individual easily [44]. Consequently, based on these measurements, the appropriate medication can be administered, or people can be transferred to the hospital when necessary. Crotty et al. utilized RPM capabilities to monitor 5367 patients with COVID-19 infection and found a substantial reduction in ICU utilization, reduced length of stay, and lower 30- and 90-day mortality when compared to patients who did not participate in active monitoring [45]. RPM has the potential to improve patient engagement and health literacy by providing real-time information that can improve outcomes, such as pruning education, which likely led to improvement in oxygenation requirements and improved outcomes [45].

AI and ML are also improving cardiovascular health through predictive analytics. Predictive analytics is the use of data, statistical algorithms, and machine learning techniques to identify the likelihood of future outcomes based on historical data. In the case of cardiovascular health, predictive analytics can be used to identify patients who are at high risk of cardiovascular disease [46, 47]. By using data from EHR, wearable devices, and other sources, healthcare professionals can identify patterns and trends such as low heart rate variability (HRV) that may indicate a higher risk of subsequent cardiovascular events (14). AI and ML algorithms can be also used to analyze HRV signals to track and evaluate the effectiveness of therapeutic interventions such as HRV biofeedback. Burlacu et al. outlined a systematic review on the beneficial effects of HRV-biofeedback, a slow breathing technique, on different cardiovascular diseases such as arterial hypertension, heart failure, and coronary artery disease. HRV modulation can be implemented in high-risk patients to significantly reduce stress levels and improve autonomic nervous system function and cardiovascular endpoints [48].

5.1 Challenges of AI *in vital* sign monitoring

With the increasing utilization of smart medical devices, there is a growing risk of sensitive medical data being accessed [49] or stolen. To address this concern, it is necessary to implement robust security measures such as encryption and access controls to ensure that personal information is properly protected. Rajasekaran proposed that the IoHT must include several key features such as trust ability, low transmission latency, security, confidentiality, integrity, and availability [50]. They proposed a blockchain-based anonymous privacy-preserving authentication scheme to preserve the key features outlined above.

Additionally, the lack of interoperability of the different wearable devices is one of the biggest hurdles that we need to overcome. By enabling different devices to share data, interoperability opens the door to new possibilities for personalized healthcare. For example, a wearable health device that tracks a user's physical activity can share data with another device that monitors their heart rate. This data can then be combined to create a more complete picture of the user's health, helping healthcare providers make more informed decisions about treatment and care. Interoperability will also help generate high-quality data that can be used to train ML algorithms.

For machine learning algorithms to work effectively, they require a large amount of high-quality data to train on. ML algorithms can be biased if the training data contains systematic inaccuracies or overrepresents one group. Straw et al. demonstrated one such bias when they reviewed Indian Liver Patient Dataset (ILPD), which is the open source data set used extensively to create algorithms that predict liver disease. Due to the under representation of females in the data set, the model demonstrated a higher false negative rate in women leading to lower disease detection in females [51]. To minimize the risk of bias, it is important to carefully select training data by using diverse and representative data sets. Additionally, the development and deployment of ML models should be guided by ethical and inclusive principles. Mccradden et al. outlined ethical principles of nonmaleficence, relevance, accountability, transparency, and justice as the foundation for the regulation of healthcare ML algorithms [52].

In inference, AI and ML have the potential to revolutionize the way healthcare is delivered. With the ability to collect vast amounts of patient data in real-time, AI algorithms can provide valuable insights into patients' health, improve the accuracy of diagnosis, detect health issues early, and improve patient engagement and health literacy. While there are still challenges to overcome such as security, interoperability of wearable devices, and ML bias, AI and ML have the potential to significantly improve patient outcomes and transform the way healthcare is delivered. Clinicians and policymakers, however, must ensure that the technology is accessible and affordable for all patients, regardless of their socioeconomic status. While there have been significant advancements in RPM technology in recent years, many patients, particularly those living in rural or underserved areas, may not have access to these tools due to cost or limited availability.

6. AI in diabetes and Glycemic control

Artificial intelligence is a fast-growing field with its applications for persons living with many chronic diseases such as diabetes. There has been global concern about the ever-increasing incidence rate of diabetes with one in two persons undiagnosed and untreated [53]. The total number of people living with diabetes is likely to rise to 643 million by 2030 and 783 million by 2045 [53]. A recent study of 300,000 patients with type 2 diabetes on medical therapy found that after 3 months, 31% of patients had discontinued their diabetes medications that number was widened to 44% by 6 months, and to 58% by 1 year [54]. Besides, about 75% of diabetic adults live in low- and middle-income countries with only 5% of those receiving thorough treatment according to guidelines [55]. The best care for diabetes is mostly hindered by lack of real-time crucial health information required to make necessary choices with diabetes control and therapy.

Today, advances in AI have introduced a shift in diabetes care from conventional management approaches to targeted data-driven precision care. There is a spectrum of interventions spread across different care processes in diabetes. AI is not only being applied to predict diabetes risk utilizing genetic data and to diagnose diabetes *via* electronic health record data in clinical decision support but it is also transforming diabetic care and predicting the potential sequelae of diabetes such as nephropathy and retinopathy. Such solutions have enhanced the workflow of both medical staff and patients.

6.1 How is AI utilized in diabetic care?

To help fight diabetes disease and improve its management, AI can play a vital role in diabetic care at many different levels discussed below that can benefit both providers and patients in a team-oriented approach.

6.1.1 Diabetes prediction

AI can help diagnose diabetes noninvasively and proactively by identifying a subset of populations with the highest risks at a pre-illness stage. Though diabetes prediction models have been generated by conventional statistics, machine learning (ML) can maximize the predictive performance of conventional models to the next level [56]. Algorithms built by ML can do risk stratification by analyzing genomics, lifestyles, mental and physical health, and social media activity. Earlier detection and intervention for at-risk individuals could decrease the incidence of diabetes, and the financial costs associated with uncontrolled diabetes.

6.1.2 Lifestyle guidance for diabetes patients

Monitoring glucose levels in real-time is being done using wearable devices and continuous glucose monitoring systems of patient symptoms and biomarkers. Continuous glucose monitors (CGM), which are now frequently used by diabetics, acquire a large amount of data that has previously been underutilized. The amount of glucose in the fluid inside the body is measured by CGM. In certain circumstances, the sensor is glued to the back of the arm or is implanted under the skin of the belly rapidly and painlessly. The information is then sent to a wireless-pager-like monitor through a transmitter on the sensor [57].

CGM sensors can be divided into two main categories: Professional CGM sensors and real-time CGM sensors (rtCGM) [58]. Professional CGM sensors are prescribed by healthcare professionals usually for limited periods of time, they record glucose concentration data in blinded modalities (i.e., the patient cannot visualize the data in real-time), and they allow the healthcare professional to retrospectively review the patient's glycemic trends and make therapy adjustments. Conversely, with real-time CGM sensors (rtCGM) the recorded data are accessible in real-time to the patient, who can use these data for improved decision-making in the daily management of Type 1 diabetes. AI can enable patients to decide what to eat or drink and what level of physical exercise is suitable.

6.1.3 Insulin injection guidance

AI can be used to provide personalized recommendations for insulin dosage besides meal planning based on glucose levels, physical activity, and other factors. The CGM sensors provide in real-time, every 1–5 minutes, the current blood glucose concentration, and its rate-of-change, two key pieces of information for improving the determination of exogenous insulin administration and the prediction of forthcoming adverse events such as hypo−/hyper-glycemia.

The most popular rtCGM sensors are minimally invasive electrochemical sensors that measure interstitial glucose concentration by a small transcutaneous electrode placed under the skin of the abdomen, or the arm. Some insulin pumps can be integrated with rtCGM sensors into the so-called closed-loop system in which a control algorithm automatically adjusts the insulin dose based on the glucose concentration measured [58]. A recent randomized controlled trial using an automated AI-based decision support system for insulin showed statistically no difference in the percentage of time spent within the target glucose range with no adverse events reported in patients on remote AI arm versus three adverse events in patients on remote adjustments by physicians' arm [59].

6.1.4 Glycemic adverse events detection

Particularly, pediatric and geriatric patients are at risk of severe hypo- and hyperglycemic events. Many noninvasive techniques using AI-based algorithms are being proposed and tested to detect glycemic events. Scientists have developed an AI system that will detect hypoglycemia or low glucose through data collected *via* CGM, which is employed for detecting low glucose levels using a noninvasive wearable sensor.

Glycemic events, using ECG signals collected through noninvasive devices, are also being tested [60]. ECG-based glucose detection can be more practical for diabetic patients with comorbidities who are more familiar with ECG monitoring for other clinical monitoring [61]. It could also be more favorable for prediabetics who might be more aware due to commercial use in fitness or sports applications. Such AI assistants also provide statistics and communicate with the care provider in the case of an emergency.

6.1.5 Monitoring diabetes complications

Progress in AI for improving screening and detection of diabetic retinopathy, macular edema, and foot ulcers can transform the gaps in clinical care. The cost of screening and limitation on human and equipment resources is still challenging despite adoption of telemedicine especially in developing countries. The early detection of complications can protect patients from dangerous stages that may later cause blindness and foot amputations. Providers are successfully leveraging deep learning to automate the diagnosis of retinopathy with high accuracy and specificity levels [62].

6.1.6 Patient engagement

Improving patient engagement and self-management through immersive technology, virtual coaching, and educational programs can shift disease courses to better outcomes. Face-to-face educational programs are followed in less than 10% of newly diagnosed people, but the emergence of digital health has given them the opportunity to overcome the challenges of lower engagement and participation from patients [63]. A statewide survey study in Indianapolis found that about 50% of people use technology to communicate with providers [63]. Telemedicine, *via* various telehealth portals, is now accepted as the necessary new normal and is expected to grow by 33% from 2019 to 2026 thus reaching $ 185.6 billion by 2026 [64]. Patients involved in their healthcare will experience better long-term health outcomes and incur lower costs, so there is a push toward promoting greater patient engagement.

6.2 Challenges in AI of diabetic care

Though there are many diabetic AI apps and devices everywhere, however, there has been a lower uptake in the long-term engagement of digital health technologies [65]. Even with a slower understanding of technologies, digital data collected from diabetic patients is growing exponentially. Data is the key to creating better AI insights, but it can be very easy to get exhausted by big data. Besides, data collected by wearables has constraints around their integration into existing systems. It also raises concerns about data privacy, security, and even legal hurdles.

Our ambition should be to create comprehensive and relevant solutions to enhance the usability of AI-based tools with evidence-based models in collaboration with all stakeholders including patients. Effectiveness will depend on the rapidity of construction and modification of new apps, devices, and sensors according to improve diabetes experience for patients and organizational needs. The resolution of such challenges will depend on adequate scientific research and regulation.

7. Conclusion

In conclusion, artificial intelligence (AI) has the potential to revolutionize healthcare management and provide tremendous benefits to healthcare organizations and patients alike. AI can help healthcare organizations gain insights into data that would otherwise be difficult to obtain, provide real-time decision support and recommendations, automate mundane tasks, improve diagnosis and treatment accuracy, monitor patient health, predict future health outcomes, and improve communication between healthcare professionals and patients. As AI continues to advance, healthcare organizations must take advantage of its many benefits and integrate the technology into their systems to ensure they are staying competitive in an ever-changing healthcare landscape.

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References

[1] Esteva A et al. A guide to deep learning in healthcare. Nature Medicine. 2019;**25**(1):24-29

[2] Miotto R et al. Deep learning for healthcare: Review, opportunities and challenges. Briefings in Bioinformatics. 2018;**19**(6):1236-1246

[3] Shen Y et al. ChatGPT and other large language models are double-edged swords. Radiological Society of North America. 2023;**2023**:230163

[4] Hosny A et al. Artificial intelligence in radiology. Nature Reviews Cancer. 2018;**18**(8):500-510

[5] Makary MS. Artificial intelligence in radiology: Current applications and future technologies. The Journal. 2021;**21**(4):205-208

[6] Santos MK et al. Artificial intelligence, machine learning, computer-aided diagnosis, and radiomics: Advances in imaging towards to precision medicine. Radiologia Brasileira. 2019;**52**:387-396

[7] AI in Radiology. 2022

[8] Gandhi Y. 8 applications of AI in Radiology. Analytics Steps. 31 Mar 2022. Available from: https://www.analyticssteps.com/blogs/8-applications-ai-radiology

[9] Oren O, Gersh BJ, Bhatt DL. Artificial intelligence in medical imaging: Switching from radiographic pathological data to clinically meaningful endpoints. The Lancet Digital Health. 2020;**2**(9):e486-e488

[10] Will AI. Replace radiologists? Intelerad, in Interlerad. May 13, 2022

[11] Jin D, Harrison AP, Zhang L, Yan K, Wang Y, Cai J, et al. Chapter 14 - Artificial intelligence in radiology. In: Xing L, Giger ML, Min JK, editors. Artificial Intelligence in Medicine. Academic Press; 2021. pp. 265-289. DOI: 10.1016/B978-0- 12-821259-2.00014-4. ISBN 9780128212592. Available from: https://www.sciencedirect.com/science/article/pii/B9780128212592000144

[12] Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL. Artificial intelligence in radiology. Nature Reviews Cancer. Aug 2018;**18**(8):500-510. DOI: 10.1038/s41568-018-0016-5. PMID: 29777175; PMCID: PMC6268174

[13] Bi WL et al. Artificial intelligence in cancer imaging: Clinical challenges and applications. CA: A Cancer Journal for Clinicians. 2019;**69**(2):127-157

[14] Wang S, Xiao T, Liu Q, Zheng H. Deep learning for fast MR imaging: A review for learning reconstruction from incomplete k-space data, Biomedical Signal Processing and Control. 2021;**68**:102579. DOI: 10.1016/j.bspc.2021.102579. ISSN 1746- 8094. Available from: https://www.sciencedirect.com/science/article/pii/S1746809421001762

[15] T., N., Top ten issues on liability and regulation of Artificial Intelligence (AI) systems. Top Ten Issues on Liability and Regulation of Artificial Intelligence (AI) Systems, A.o.C.C. (ACC), Editor. August 2, 2021

[16] Bak M et al. You can't have AI both ways: Balancing health data privacy and access fairly. Frontiers in Genetics. 2022;**13**:1490

[17] Sajid H. Ai in radiology: Pros & cons, applications, and 4 examples, in V7. 2023

[18] Korngiebel DM, Solomonides A, Goodman KW. Ethical and Policy Issues. In: Cohen TA, Patel VL, Shortliffe EH, editors. Intelligent Systems in Medicine and Health. Cognitive Informatics in Biomedicine and Healthcare. Cham, Springer; 2022. DOI: 10.1007/978-3-031-09108-7_18

[19] Ahuja AS. The impact of artificial intelligence in medicine on the future role of the physician. PeerJ. 2019;**7**:e7702

[20] AAMC, Number of people per active physician by specialty

[21] Smith G, Funk J. Ai has a long way to go before doctors can trust it with your life in Quartz. . June 4, 2021

[22] Pesapane F, Codari M, Sardanelli F. Artificial intelligence in medical imaging: Threat or opportunity? Radiologists again at the forefront of innovation in medicine. European Radiology Experimental. 2018;**2**:1-10

[23] Hardy M, Harvey H. Artificial intelligence in diagnostic imaging: Impact on the radiography profession. The British Journal of Radiology. 2020;**93**(1108):20190840

[24] Duong MT et al. Artificial intelligence for precision education in radiology. The British Journal of Radiology. 2019;**92**(1103):20190389

[25] Biswas S. Artificial intelligence in radiology education. International Journal of Radiological Radiational Therapy. 2023;**10**(1):1-3

[26] Spear LG et al. Rethinking clinical trial radiology workflows and student training: Integrated virtual student shadowing experience, education, and evaluation. Journal of Digital Imaging. 2022;**35**(3):723-731

[27] Uppot RN et al. Implementing virtual and augmented reality tools for radiology education and training, communication, and clinical care. Radiology. 2019;**291**(3):570-580

[28] Wiggins WF et al. Preparing radiologists to lead in the era of artificial intelligence: Designing and implementing a focused data science pathway for senior radiology residents. Radiology: Artificial Intelligence. 2020;**2**(6):e200057

[29] Lai L, Wittbold KA, Dadabhoy FZ, Sato R, Landman AB, Schwamm LH, et al. Digital triage: Novel strategies for population health management in response to the COVID-19 pandemic. Healthcare (Amsterdam, Netherlands). 2020;**8**(4):100493. DOI: 10.1016/j.hjdsi.2020.100493

[30] Ebrahimian S et al. FDA-regulated AI algorithms: Trends, strengths, and gaps of validation studies. Academic Radiology. 2022;**29**(4):559-566

[31] Estrada EG. Triage systems. Nursing Clinics of North America. 1981;**16**(1):13-24

[32] Sharafat AR, Bayati M. PatientFlowNet: A deep learning approach to patient flow prediction in emergency departments. IEEE Access. 2021;**9**:45552-45561

[33] Tool Developed to assist in Triage in the Emergency Department in John Hopkin news and publication. 2022

[34] Chen C-H et al. Emergency department disposition prediction using a deep neural network with integrated clinical narratives and structured data. International Journal of Medical Informatics. 2020;**139**:104146

[35] Goto S et al. Artificial intelligence to predict needs for urgent

revascularization from 12-leads electrocardiography in emergency patients. PLoS One. 2019;**14**:e0210103

[36] Than MP et al. Machine learning to predict the likelihood of acute myocardial infarction. Circulation. 2019;**140**(11):899-909

[37] Tayal V, Raio C. ACEP Policy Statement-Ultrasound Guidelines: Emergency. Point-of-Care, and Clinical Ultrasound Guidelines in Medicine. 2016

[38] Shokoohi H et al. Enhanced point-of-care ultrasound applications by integrating automated feature-learning systems using deep learning. Journal of Ultrasound in Medicine. 2019;**38**(7):1887-1897

[39] Fleuren LM et al. Machine learning for the prediction of sepsis: A systematic review and meta-analysis of diagnostic test accuracy. Intensive Care Medicine. 2020;**46**:383-400

[40] Murphy SL, Xu J, Kochanek KD. Deaths: final data for 2010. National Vital Statistics Reports. 8 May 2013;**61**(4):1-117. PMID: 24979972

[41] Islam MM et al. Prediction of sepsis patients using machine learning approach: A meta-analysis. Computer Methods and Programs in Biomedicine. 2019;**170**:1-9

[42] Mao Q et al. Multicentre validation of a sepsis prediction algorithm using only vital sign data in the emergency department, general ward and ICU. BMJ Open. 2018;**8**(1):e017833

[43] Shickel B et al. DeepSOFA: A continuous acuity score for critically ill patients using clinically interpretable deep learning. Scientific Reports. 2019;**9**(1):1879

[44] Saeed U et al. Machine learning empowered COVID-19 patient monitoring using non-contact sensing: An extensive review. Journal of Pharmaceutical Analysis. 2022;**12**(2):193-204

[45] Crotty BH et al. Hospitalization outcomes among patients with COVID-19 undergoing remote monitoring. JAMA Network Open. 2022;**5**(7):e2221050-e2221050

[46] Huang J-D et al. Applying artificial intelligence to wearable sensor data to diagnose and predict cardiovascular disease: A review. Sensors. 2022;**22**(20):8002

[47] Fang S-C, Wu Y-L, Tsai P-S. Heart rate variability and risk of all-cause death and cardiovascular events in patients with cardiovascular disease: A meta-analysis of cohort studies. Biological Research for Nursing. 2020;**22**(1):45-56

[48] Burlacu A et al. Influencing cardiovascular outcomes through heart rate variability modulation: A systematic review. Diagnostics. 2021;**11**(12):2198

[49] DeepMind faces legal action over NHS data use Oct 2021

[50] Rajasekaran AS et al. Blockchain enabled anonymous privacy-preserving authentication scheme for internet of health things. Sensors. 2022;**23**(1):240

[51] Straw I, Wu H. Investigating for bias in healthcare algorithms: A sex-stratified analysis of supervised machine learning models in liver disease prediction. BMJ Health & Care Informatics. 2022;**2002**:29

[52] McCradden MD et al. Patient safety and quality improvement: Ethical principles for a regulatory approach to bias in healthcare machine learning. Journal of the American

Medical Informatics Association. 2020;**27**(12):2024-2027

[53] Federation I. IDF Diabetes Atlas, tenth. International Diabetes. 2021

[54] Latts L. ADA/IBM Watson Health Study (N> 300,000) finds that nearly 60% of people with T2D discontinue therapy after one year. American Diabetes Association 78th Scientific Session. 2018

[55] Flood D et al. The state of diabetes treatment coverage in 55 low-income and middle-income countries: A cross-sectional study of nationally representative, individual-level data in 680 102 adults. The Lancet Healthy Longevity. 2021;**2**(6):e340-e351

[56] Nomura A et al. Artificial intelligence in current diabetes management and prediction. Current Diabetes Reports. 2021;**21**(12):61

[57] A., P. How predictive models of AI & Machine Learning Can Transform Diabetes Care. mddionline. com. 15 June 2022

[58] Vettoretti M et al. Advanced diabetes management using artificial intelligence and continuous glucose monitoring sensors. Sensors. 2020;**20**(14):3870

[59] Nimri R et al. Insulin dose optimization using an automated artificial intelligence-based decision support system in youths with type 1 diabetes. Nature Medicine. 2020;**26**(9):1380-1384

[60] Andellini M et al. Artificial intelligence for non-invasive glycaemic-events detection via ECG in a paediatric population: Study protocol. Health and Technology. 2023;**2023**:1-10

[61] Porumb M et al. Precision medicine and artificial intelligence: A pilot study on deep learning for hypoglycemic events detection based on ECG. Scientific Reports. 2020;**10**(1):170

[62] Nanegrungsunk O, Ruamviboonsuk P, Grzybowski A. Prospective studies on artificial intelligence (AI)-based diabetic retinopathy screening. Annals of Translational Medicine. 2022;**2022**:24

[63] Health & Social Care Information Centre. National Diabetes Audit – 2013-2014 and 2014-2015: Report 1, Care Processes and Treatment Targets [Internet]. NHS Digital. 2015

[64] globenewswire.com, Telemedicine Market to Reach USD 185.66 Billion by 2026 June 2022

[65] Pal K et al. Digital health interventions for adults with type 2 diabetes: Qualitative study of patient perspectives on diabetes self-management education and support. Journal of Medical Internet Research. 2018;**20**(2):e40