TRANSFORMING HEALTHCARE DECISION-MAKING: THE ROLE OFAI IN EVIDENCE-BASED MEDICINE

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KEYWORDS

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ABSTRACT:

Artificial intelligence (AI) integrated in health care portends to be a needle of transformative potential in providing evidence-based medicine as advancements in diagnostic precision and personalized treatment and patient care optimization. This paper explores the cutting edge of technologies including machine learning, natural language processing and predictive analytics in the pivotal role of AI in EBM. Through AI analysis of vast datasets, the methodology supports the use of clinical decision making that reduces human error and enables the development of optimal, personalized treatment plans for each patient. And we survey current AI uses in healthcare, such as AI based diagnostic tools, AI based predictive disease progression models, and AI based clinical decision support systems (CDSS). We also discuss the challenges and the ethical aspects of AI integration, especially issues related to data privacy, algorithmic bias and require for effective regulatory measures. We show how AI can strengthen EBM in practice through case studies and real world examples. Finally, the paper has a look forward to future prospects and novel trends in AI showing p.s.otential to transform healthcare delivery beyond even what is imagined today. Included are advances in the AI algorithms used in health care, the increased inter operability of AI systems in health care infrastructures, and the opportunity for AI to enable broader and more comprehensive, and thus inclusive, medical research. Our results highlight the importance of systems where technological innovation is carefully balanced with ethical considerations in realizing the full potential in AI for transforming healthcare clinical decision making and patient outcomes.

1.INTRODUCTION

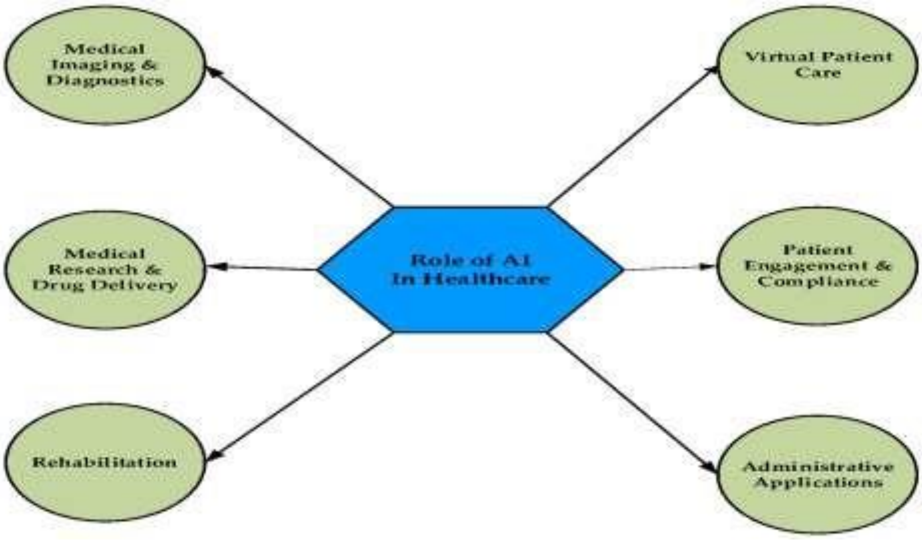
1.1 Background and Significance of Evidence-Based Medicine (EBM)

Evidence-based medicine (EBM) is the conscientious use of the most current and relevant clinical evidence in decision making about the care of individual patients. The approach discussed stresses the use of clinical expertise, patient preferences, and most critical research evidence to achieve optimal health outcomes (Sackett et al., 1996). For the last few decades, EBM has been the central pillar of post modern healthcare, helping establish improved clinical practices and patient care. By providing scientifically based evidence, healthcare providers can make informed decisions, thus eliminating variations and improving the efficacy of treatment (Guyatt et al. 2015). Of particular interest is the promise of EBM to improve the quality of care by decreasing errors, increasing patient outcomes and optimizing resource use. As the scope of medical knowledge is in rapid flux, clinicians' skills at accessing and using current evidence are critical for providing optimal, patient targeted care. Often, however, the complexity of healthcare data is increasing as is the time constraints on the part of the clinicians which limits the full implementation of EBM in clinical practice (Haynes et al., 2002). The need for innovative approaches to facilitate evidence based decision making is highlighted in this challenge.

1.2 Overview of Artificial Intelligence (AI) in healthcare

Artificial intelligence (AI) is one of the software example that simulates human intelligence in the machine that was designed to do things, which machines requires human intelligence to do such as learning, reasoning and problem solving. Machine learning (ML), natural language processing (NLP) and predictive analytics are used in the health care arena to analyze massive data and render insights that may assist the diagnosis, plan cancer treatment, and routinely monitor patients (Topol, 2019). With great potential to greatly improve the way healthcare delivery, these technologies can help the healthcare professionals make more accurate and timely decisions. We are already seeing a huge impact of AI on all areas of healthcare. For example, given the rise of AI algorithms which can analyze medical imaging to see potential signs of cancer or other condition earlier than a human can, AI algorithms seem to outperform a human clinician for detecting early signs of conditions such as cancer (Rajpurkar et al., 2017). AI driven clinical decision support systems (CDSS) can aggregate large volumes of clinical data into real time evidence based recommendations aimed at streamlining clinicians decision making (Jha et al., 2018). However, intersection of EBM's base on scientific evidence and AI's computational power may revolution healthcare by improving diagnostic accuracy, personalizing therapy and ultimately improve outcomes for patients.

Figure 1: Role of AI in Healthcare



1.3 Aim and Objectives of the Paper

This paper aims to discuss how artificial intelligence can transform evidence based medicine and how it could help enhance the healthcare decision making. This paper therefore explores how integrating AI technologies into EBM practices can deal with challenges now faced by healthcare systems: the dominance of clinical data, the requirement for personalised treatment plans, and pressure to improve patient outcomes.

The key objectives of the paper are:

1. Specifically, the proposals are to look at how machine learning, natural language processing, and predictive analytics are able to augment the practice of evidence-based medicine.

2. To identify the potential of applying informs and enhancing clinical decisions with AI primarily in diagnostics, treatment personalization and patient support.

3. In order to explore weakness and ethical issues involving the application of AI in EBM people must consider data protection, algorithmic bias, the lack of appropriate rules, and regulations.

4. To evaluate the potential of AI in EBM in the next years, the trends, developments, and innovative approaches are used in this process.

5. For the purpose of making suggestions to the healthcare practitioners, policymakers, and researchers about how to implement the AI based practice in the evidence based practice to enhance the healthcare.

2. LITERATURE REVIEW

2.1 Evolution of Evidence-Based Medicine

Identifying the sources of the best available evidence and integrating it into clinical practice is what is known as EBM The science of EBM began developing formally in the 1990s, after the groundwork laid by Dr David Sackett and his team from McMaster University. The earlier operationalisation of EBM was described by Sackett et al. (1996) as “the integration, on purpose and following a clear procedure, of the best research evidence with other sources of information to guide decisions about individual care”. The idea of EBM was to translate the current and best; available research to practice and eliminate unwarranted clinical differences that diminish patient outcomes and enhance adverse events in care delivery (Guyatt et al., 2015). EBM has gradually evolved to be a robust and integral element of today’s health care systems envisaged to revolutionalise the health care delivery system.

Over the time, the definition of EBM broadened from using solely trial data in order to include observational studies, systematic reviews, as well as clinical experience. It has facilitated a move to using an integrated medical model which integrates the researcher evidence with the values and experience of the patient and the clinician involved (Greenhalgh, 2014). Some significant changes in EBM practice carry on to expand over time, they include clinical guidelines, clinical decision support and the implementation of patient-reported associations in the delivery of care [Haynes et al., p 12]. However, Tannenbaum et al. (2017) noted that traditional EBM was subjected to few limitations in regard to data overload, the amount of time needed when assessing the evidence, as well the nature of varied individual patients, which require particular approaches to treatment.

2.2 Current Applications of AI in Healthcare

The use of AI in healthcare is on the rise because of the effectiveness of dealing with large volumes of data to support clinical decision processes. There is no doubt that the application of AI software is especially in medical imaging because AI algorithms, including the deep learning model, can accurately interpret radiographs, CT, and MRI. It turns out that AI may be more effective in diagnosing primary pathologies, such as pneumonia, breast cancer or skin lesions than radiologists (Rajpurkar et al., 2017; Esteva et al., 2017). Furthermore, AI is

employed in prognosis analysis of the disease's trend through patients' data in the EHRs to prompt appropriate care and course of treatment, specific to the individual (Miotto et al., 2016). Another is in the application of clinical decision support systems (CDSS) where an artificial intelligent tool advises clinicians in real-time about what they ought to do based on all accessible knowledge at any given time. For example, IBM's Watson for Oncology helps oncologists in creating individual cancer treatment options based on the patient's information, and outcomes of up-to-date research (Jha et al, 2018). Six categories of AI technology include diagnostic, treatment, patient simulation, knowledge representation, predictive models, and decision support (Choi et al., 2016).
Incorporation of AI in health systems has thus served to boost the coordinated practice of EBHC by first minimising the burden that comes with analysing large data sets, thereby maximising diagnostic and therapeutic precision (Topol, 2019). Nevertheless, the following issues remain critical to the wider use of AI: Data quality, the issue of bias in algorithms, and best practice variation across healthcare organisations.

2.3 Challenges and Limitations in Traditional EBM Practices

Though EBM has created a positive impact and transformation of the healthcare system, traditional EBM process has certain drawbacks. This brings us to the first of our challenges: the information overload that clinicians face when seeking to engage with the latest evidence. Due to publication of thousands of articles daily, it becomes harder for the health care providers to search and identify the research articles (Haynes et al., 2002). The plethora of information proves confusing and time-consuming hence becoming difficult for clinicians to incorporate the existing evidence in their practice (Tannenbaum et al., 2017).
A second weakness seen in the traditional EBM is based on RCTs and systematic reviews as the strongest evidence. Even though these studies give meaningful information their results could not provide detailed information about the patient's conditions and possibilities of his/her body responding to a certain disease or kind of treatment due to the presence of other diseases, genetic and lifestyle factors. Consequently, criticism of EBM has arisen stating that EBM is not sufficiently individualized (Schwartz & Mates, 2004). It suggests that there is a greater requirement to focus on the patient's characteristics and include them into the decision making factor.
However, the use of evidence in practice is frequently delayed by the time it takes to undertake rigorous research and then to disseminate the results (Greenhalgh, 2014). This time lag means very often outdate evidence is used in patient care as recent discoveries in the medical field may not have been utilized. Furthermore, clinicians can be challenged when applying the evidence to practice due to the complexity or irrelevancy of the findings to the population they deal with (Grol & Grimshaw, 2003).
Evidenced based medicine has revolutionized the practice of medicine with traditional approaches faced with challenges, in relation to flood of information, issues of generality nature and time lag in implementing evidence. AI provides the solutions for these challenges since it can provide the decision support that is more personal, accurate, and in flowing time. However, AI has to be incorporated into health care systems cautiously to eliminate the barriers of ethic, regulation as well as technology.

Table 1:Role of AI in evidence-Based Medicine

Aspect	Traditional Evidence-Based medical (EBM)	Role of AI in EBM	Examples / Applications

Definition and focus	Focus on using clinical evidence (RCTs, systematic reviews) for decision-making in patient care	Uses AI algorithms to analyze clinical data and assist in decisionmaking	- AI-driven clinical decision support systems (CDSS)
Data Processing	Relies on clinicals manually reviewing large volume of medical literature to	AI automates data processing, enabling faster and more accurate evidence analysis, reducing the	- Machine learning dat analy s for
	identify relevant evidence	manual burden on clinicals	and pattern recognition
Personalization	EBM is often generalization, not fully addressing individual patient variability, such as genetic or comorbidities	AI enables more personalized approaches by analyzing individual patient data (e.g., genomics, lifestyle) for tailored treatments	- AI in personalized cancer treatment (e.g., IBM Watson for oncology)
Clinical Decision support	Provides recommendations based on existing evidence but may struggle with integrating real-time data	AI-powered CDSS provide real-time, evidence-based recommendations by synthesizing data from multiple sources	- AI-based drug recommendations, real-time diagnostic assistance
Outcome prediction	Limited predicting patient outcomes due to reliance on historical data and clinical expertise	AI-uses predictive analytics to forecast patient outcomes, enabling early interventions and better care planning	- Predictive models for disease progression (e,g., heart disease, cancer)
Implementation in practice	EBM implementation is often slow due to time lag in translating research into practice and data accessibility issues	AI reduces the time lag by quickly analyzing data and updating clinical recommendations in real-time	- Real-time patient monitoring and adaptive treatment strategies
Challenges	- Information overload due to vast amounts of new research. - Generalization of evidence not always applicable to all patients	- Data quality issues (e.g., incomplete or biased data), - Ethical concerns around AI decisions and data privacy	- AI`s dependence on high-quality, unbiased data. - Addressing algorithmic bias

Data sources	Primarily clinical trials, systematic reviews, observational studies, and expert consensus	Utilizes data from electronic health records (EHR), wearables, genomics data, and medical imaging	-Use of EHR for personalized treatment plans. - AI in medical imaging (e.g., radiology)
Ethical considerations	Ethical issues include informed consent, patient autonomy, and the risk of overtreatment	Ethical concerns with AI include Algorithmic transparency, biases, and patient data privacy	- Need for regulatory frameworks for AI in healthcare

3. AI TECHNOLOGIES IN HEALTHCARE

3.1 Machine Learning Algorithms

The foundation of AI in supporting healthcare's pursuits is composed of ML techniques that allow systems to draw conclusions without prior predetermined instructions. These algorithms are capable of processing massive data like medical data, imaging data and sensor data and then make clinical decisions. As were mentioned above, ML algorithms applied in healthcare are divided into supervised learning, unsupervised learning, and reinforcement learning (Rajpurkar et al., 2017). In medical imaging, Application of ML algorithms can diagnose disease such as cancers, cardiac diseases and neurological diseases because by working over a large set of images and processing data, there are distinctive features that might not be apparent to the clinicians (Esteva et al., 2017). Furthermore, in the application of predictive modeling, machine learning makes predictions on patient outcomes classified via algorithms from past data (Choi et al., 2016). Such applications have evidenced the enhancements in setting pinpoint diagnoses, achieving maximum speedy results andavailability of individualized plans of treatments.

3.2 Natural Language Processing

Natural Language Processing (NLP) is another key AI tech application about which computers are able to understand, evaluate and generate human languages. NLP can extract artefacts and patterns from natural language textual data such as clinical reports, research articles, and patents documents written in the free text style (Joulin et al., 2017). Thus, through analyzing this text, NLP algorithms can help defining medical information, trends and patterns which are not easily detectable in a manual manner.NLP is of great importance in clinical decision making support systems which can help the physicians to make informed evidence based decisions by extracting knowledge from the electronic health records and scientific literature. For instance, NLP used in Software like IBM Watson which combines the massive and unstructured medical information with recommendations to the clinician. Further, for bed-side patient monitoring NLP helps in recognizing patient and caregiver spoken interactions for assessing clinical condition without burdening the clinicians.

3.3 Predictive Analytics and Data Mining

A predictive analytics and data mining are examples of Artificial Intelligence techniques used in healthcare to process large volumes of health data for the purpose of making prognoses, to identify patients at risk and suggest appropriate interventions. Due to its ability to predict events in an individual patients' life such as disease exacerbation, risk of hospitalization, and ability to respond to such events when they occurred, predictive analytics is valuable (Choi et al., 2016). Another related method is so called data mining, which implies the study of vast sets of information to reveal the existing connexions between them. Oppositely, in a medical field, data mining methods can detect potential indicators of chronic diseases, manage resources and abide by new drug development (Miotto, 2016). These techniques use EHRs, sensors, and genomics to support clinicians when determining which treatment strategies are likely to be most beneficial to particular patients. Analytical processes of data predictive and analysis of data mining is making difference in healthcare industry by bringing positive changes in terms of cost and result. For instance, the health care facilities are applying predictive analytics to reduce instances of readmission, managing human resource in healthcare and identifying patient in the hospitals that are most likely to develop other complications that are manageable thus promoting efficiency in the health care facility (Rajkomar et al., 2019).

4. ROLE OF AI IN EVIDENCE-BASED MEDICINE

4.1 Enhancing Diagnostic Accuracy

AI also contributes to improved diagnostics by processing medical information more effectively and with better precision than conventional approaches demonstrate. Artificial intelligence or precise deep learning methods can record all kinds of patterns and signs, including radiographic findings, genomics, and EHRs. AI models can be used for the diagnostic procedures concerning cancer, heart diseases, neurological disorders, etc with the higher efficiency of the diagnoses comparing to the results achieved by the human clinicians (Rajpurkar et al., 2017). For example, the biometrics using artificial intelligence algorithms has been found to recognize images from mammograms better than breast cancer diagnosing radiologists in some cases (Esteva et al., 2017). In the same way, applications like IBM Watson for Oncology examine patient information together with millions of papers and documents to come up with accurate patient diagnosis and treatment recommendations. The improve of the diagnostic accuracy brings benefits to the patients and minimizes the possibility of misdiagnosis.

4.2 Personalized Treatment Plans

AI is changing the way clinicians and pharmacologists are approaching the approach to treating patients by integrating individual patient data: genetic makeup, life preferences, and medical history. These datasets are then used by machine learning algorithms to identify what treatment approaches will be the most successful: increasing the accuracy and productivity of medical care. This approach makes the treatment more effective because the doctor takes into account different factors related to the patient status (Topol, 2019). In genomics, for instance, the use of AI means that doctors will be able to prescribe medications based on a patient’s genetic profile, and only deliver the best-suited for the person’s genetics treatment. In oncology for instance, Duan et al (2015) have shown that AI models assist in determining the right treatment plan for a patient from the genomic information obtained. Machine learning based therapies have the ability to transform highly specific fields such as oncology, cardiology, and psychiatric, as customization is quintessential for efficacy.

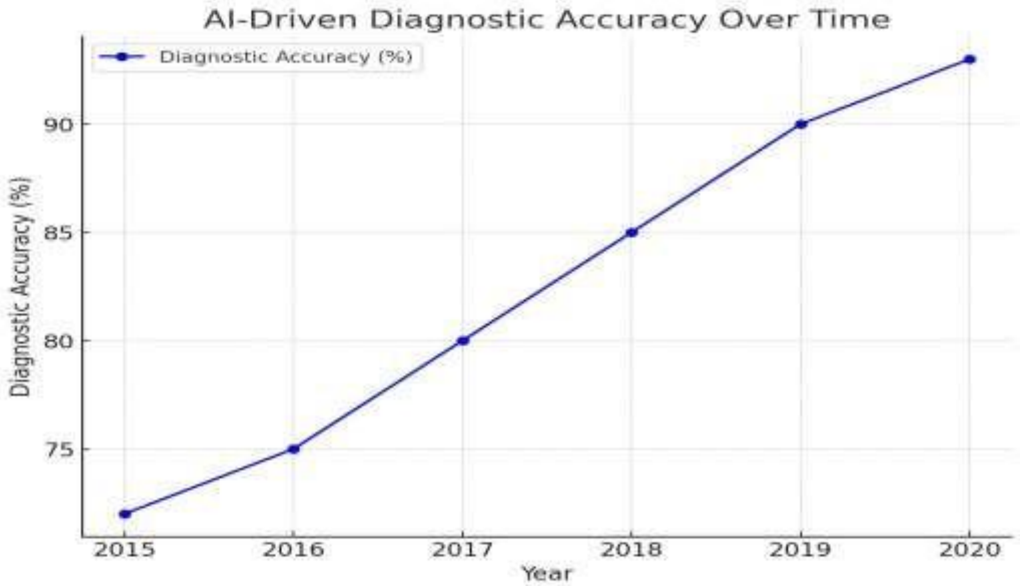
4.3 Improving Patient Outcomes

This lends credence with AI’s efficiency in increasing patients’ prognosis as an added role since it equally possesses the predetermining ability of an early disease advancement. These areas of product development give an ability to assess the patient data and determine possible health risks such as a heart attack, stroke or any diabetic issues. This prognostic function allows for early prevention of exacerbation of the mentioned diseases, which leads to an improvement in patient outcomes in general (Choi et al., 2016). For instance, AI applied in analysis of the ICU patients’ data can help in early identification of sepsis to avoid many deaths due to the condition (Goh et al., 2019). Cardiovascular risk prediction models are used in cardiology to predict heart failure and stroke risks and take preventive measures that decrease mortality high rates (Rajkomar et al., 2019). When applied to healthcare, real time patient monitoring through AI not only decreases the rate of AEs but also increases the healing rate of patients and decreases the cases of readmissions.

4.4 Case Studies and Examples

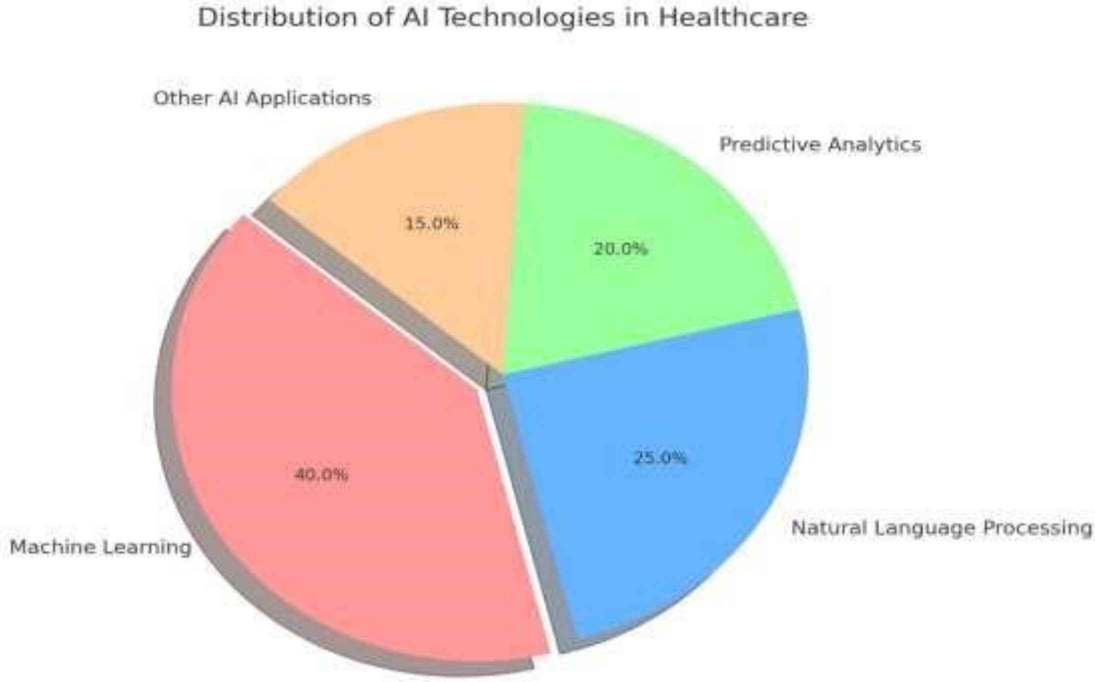
Many examples given in the literature describe how AI impacts evidence-based practice of medicine. One of them is AI in oncology where IBM Watson for Oncology has been implemented in different healthcare center to provide evidence-based decision making to oncologists. Based on medical records, clinical trials and scientific publication it recommends the treatment plans for cancer patients (Somashekhar et al., 2018). Another interesting application is of deep learning in diagnosing the diabetic retinopathy. Gulshan et al. (2016) showed that AI algorithms that were trained based on the retinal images yielded an accuracy of diagnosis that is equal to that of the ophthalmologists. This has made it possible to arrive at the diagnosis of diabetic retinopathy more efficiently and accurately in areas of limited resource and or specialized physicians. In addition, the use of AI within advanced predictive analytics most likely in patient outcomes in Intensive Care Units (ICUs). For instance, the machine learning model worked in Mount Sinai Health System helped identify patients at risk of clinical worsening in real time, thereby enhancing decisions as well as management (Rajkomar et al., 2019).

Figure 1:AI-Driven Diagnostic Accuracy Over Time



A line graph showing the progression of AI-driven diagnostic accuracy over time. The X-axis represents the years, and the Y-axis shows the diagnostic accuracy percentage

Figure 2: Distribustion of AI Technologies in Healthcare



A pie chart to demonstrate which of the AI technologies is present in the healthcare industry. All of the bolded sections represent a different AI application and its place in a health care setting and the relative size of the specific issues represented by each section are given in percentages.

Table 2: AI technology in Healthcare

AI Technology	Role in Healthcare	Percentage (%)
Machine learning	Diagnostic accuracy, pattern recognization ,	40
Natural Language processing	Extracting insights from unstructured data, clinical decision support	25
Predictive Analytics	Predicting patient outcomes, identifying high-risk patient	20
Other AI Applications	Various applications including administrative tasks, drug discovery	15

5. INTEGRATION OF AI AND EVIDENCE-BASED MEDICINE

AI is rapidly changing the process of applying EBM by enhancing decision support systems along with making procedures more effective and faster in terms of medical research. In various applications, principally the optimization and direction of the clinical decision making process, AI is assisting clinicians to provide recommended, individualised care based in principles of EBM.

5.1 Workflow Integration

AI is anticipated to revolutionise health care by eliminating repetitious tasks to improve clinical operations. From amending records on patients to enhancing teamwork, AI can bring efficiency to healthcare utilization and free more care time for the general population. Artificial intelligence s can be easily implemented in the EHRs system and other hospital information systems so that ensures the easy flow of patient information. Machine learning algorithms can also help to predict who is at risk, so that healthcare workers can focus on those individuals who require their attention most, that is to enhance general organizational efficiency (Rajkomar et al., 2019). AI-embedded practice can still pose challenges such as how to train the clinicians and how to adapt to various context in contexts of distinct health facilities. Nonetheless, the authors believe that as these designing AI technologies grow in capabilities, the implementation is hoped to become easier and less requisite to disrupt the healthcare system while offering the capability of improving the quality of care and outcome in addition to lowering healthcare costs.

5.2 Clinical Decision Support Systems (CDSS)

Clinical Decision Support Systems (CDSS) are AI systems that assist clinicians in reaching evidence-based decisions for patients by presenting the latest research findings in addition to the information regarding the patient. CDSSs that are based on artificial intelligence employ algorithms to determine diagnosis, treatment and preventive measures based on details such as patient's history, laboratory results and imaging. In general, such systems are expected to assist rather than operate independently of the clinical decision making process of health practitioners. For instance, IBM Watson for Oncology is arguably one of the most famous CDS, it has been adopted to enable oncologists to choose remedy the best cancer treatment from among a host of existing treatment methodologies based on analysis of a huge amount of medical data and literature. Research has also found out that these systems do enhance diagnostic precision and therapy choices (Somashekhar et al., 2018). However, the effectiveness of CDSS depends on the quality of data input and compatibility of AI tools with other structures of the healthcare system.

5.3 AI in Medical Research and Clinical Trials

However, health care has many ethical issues regarding the use of artificial intelligence most specifically one main question; who is to blame for the results provided by the artificial intelligence. As an algorithm gains exposure to less outside oversight, one query emerges as to where fault lies when the system is incorrect. To whose fault does an AI system belong – the one that created it, the healthcare organizations that employ it, or the system itself? On this aspect, vagueness of how and by whom these decisions are made erodes the anticipated accountability, which is core to the adoption of these systems. However, there are lacking adequate regulatory polices that address the presence or use of artificial intelligence in the health sector. Technological development if fast tends to pressure the legal frameworks on health care hence exposing patient safety to risks through creating loopholes. However, the

FDA and EMA have now begun to establish regulation that would assess AI as a healthcare technology, and much more needs to be done to determine how safe, efficient, and ethically permissible AI technologies must be (European Commission, 2021)..

5.4 Data Privacy and Security

First on the list of the issues regarding the application of AI in healthcare is the problem of data protection. HCA's handle sensitive personal health information making it easy for hackers to launch attacks on them. In AI systems, the emphasis is made on the big data set employment, which may contain the patient's data, his/her medical records, diagnosis information, etc. If these datasets are not secured adequately they are prone to patient data privacy violation and malicious access to sensitive information. Despite the fact the application of AI in the healthcare sector still raises various concerns, one report by the WHO has indicated the problem of cybersecurity and called for the adoption of measures that uphold HIPAA in the United States and GDPR in the European Union in light of the continuously expanding use of digital health technologies (WHO, 2021). It is with these things in mind that the healthcare organizations must ensure that they have effective measures put in place in order to protect the data collected, some of which are regularly encrypted and have access control measures put in place to ensure that information is kept safe and secure from the outside world on a continuous basis and that the AI systems being used are also checked on regular basis to ensure patient's data is safe and secure.

5.5 Bias in AI Algorithms

Bias in AI algorithms is a significant ethical challenge that can undermine the effectiveness and fairness of AI-driven healthcare solutions. AI models are trained on large datasets, and if these datasets are not representative of the diverse patient populations, the resulting algorithms may perpetuate existing disparities in healthcare. For example, an AI model trained on a dataset predominantly composed of data from one ethnic group may perform poorly when applied to patients from different ethnic backgrounds, leading to misdiagnosis or unequal treatment. Research has shown that biases in AI can exacerbate health inequities. A study by Obermeyer et al. (2019) found that an AI algorithm used to predict healthcare needs was less accurate for Black patients than for White patients, leading to unequal distribution of healthcare resources. Addressing bias in AI requires careful selection of diverse training datasets, transparency in algorithm development, and ongoing monitoring to ensure fairness and equity in AI applications.

5.6 Ethical Implications and Regulatory Issues

Of course, the use of artificial intelligence in health care has numerous ethical questions, most notably, who is to blame for the decisions made by artificial intelligence. One issue that arises as an algorithm gets more independent is where blame lies when the system is wrong. Who should be held responsible for an AI system where it is developed, the healthcare providers who use it, or the system itself? Uncertainty of how and by whom decisions are made undermines expectations of accountability which is fundamental to the acceptance of these systems. However, there are inadequate regulatory polices that regulate the presence and application of AI in the health sector. The fast advancement in technologies tends to put pressure on the legal frameworks on health care hence creating loopholes whereby patient safety is at risk. Still, both the FDA and EMA have started creating regulatory frameworks that would evaluate AI as a healthcare technology, and much more work is required to understand how safe, effective, and ethically appropriate AI technologies can be (European Commission, 2021).

6. FUTURE PROSPECTS

The identified key area of development arises as AI becomes increasingly widespread and ever more multifaceted in its impact on the healthcare industry to support and develop the principles of EBM. This implies that the future of AI in healthcare is bright, given the fast approaching groundbreaking technologies that are likely to change the course of clinical practice, research, and practice in healthcare delivery.

6.1 Innovations on the Horizon

The field of AI in healthcare is defined by disruptive innovation that is closely associated with areas of precision medicine, statistical risk assessment and, crucially, real-time decision making. Perhaps, it is crucial innovation is the combination of AI with genomics to provide customized therapy depending on the pathogen's genotype. Machine learning can scan your DNA and look for signs of what might go wrong, and then prescribe a course of action, making it easier to develop new treatment strategies (Topol, 2019). In addition, the recent development of intelligent medical imaging through the use of AI technology is likely to improve the efficiency of the tests resulting in improved diagnose ability of diseases like cancer, cardiovascular diseases, and neurological disorders. Deep learning AI models are notable in that they are improving at understanding medical imaging with a level of accuracy in some cases superior to human clinicians when used in detecting nuanced pathology. Another developing area is the practical application of robots with AI functionality within the field of surgery; in this case, AI in a surgeon's work helps to make minimally invasive operations more precise and faster.

6.2 Potential Impact on Global Healthcare Systems

The expected adoption of AI in healthcare systems all over the world is believed to bring drastic changes mainly in the healthcare accessibility and effectiveness. It can help to lessen the workload of healthcare personnel, because particular tasks may be solved without their interference, and it can improve the use of resources in healthcare and even the capacities of diagnosis. This could be especially of advantage in areas where there are few doctors and nurse, and even fewer clinics, hospitals, and other medical facilities. AI technologies are also likely to cut cost in healthcare delivery since the resources will not only be well managed but also since human intermediation is likely to have been eliminated. For example, it can be used to help automate scheduling, billing and claims processing for patients so that healthcare givers will be free to attend to their patients. Those potentialities in connection with population health might mean that AI may help to outline individual disposition to certain diseases and intervene early, thus shifting health outcome towards less diseases and, consequently, less healthcare spending (Brynjolfsson & McAfee, 2017).

6.3 Suggestions for future work

Possible directions for the expansion of AI and healthcare investigations in the future include overcoming the current shortcomings and developing the full potential of AI solutions. There is, however, one direction that deserves additional research, which is the creation of XAI models. Such models would enable the explanation of how AI systems reach their conclusion and increase people's confidence in them, while making the AI recommendations fully compatible with professional opinion (Caruana et al., 2015). Further, studies must compare AI with other trending technologies like blockchain to guarantee data provision security, I proper patient data nutrients. There is also a lack of longitudinal studies that focus on understanding the effects of AI in patients' outcomes, healthcare expenditures and different systems' effectiveness at large. It is therefore significant for the AI researchers to join hands with healthcare professionals, policy makers and ethicist so that they will be in a position to come up with AI technologies that will be implemented in a manner that does not mis lead the world over healthcare systems.

7. CONCLUSION

Artificial Intelligence (AI) entering the field of Evidence-Based Medicine (EBM) is an innovative phenomenon that will create a revolution in the field of clinical decision making and grant improved patient care alongside a faster delivery of such care. Application of artificial intelligence as machine learning, natural language processing and, predictive analytics have evolutions of their roles to increase the accuracy of diagnosis, give precise treatment and do medical research. Over time, it is predictable that AI will take even a greater role in the health care sector providing more sophisticated solutions to diseases preventions and treatments.
This research paper has benefited from the analysis of the importance of AI in enhancing the accessibility of EBM in healthcare delivery systems. Other highlighted discoveries are increased diagnostic precision owing to the use of AI and better treatment management, as well as improved decision-making process. AI artificial intelligence has played a critical role in medical research in advancing the development of drugs and clinical trial and delivering personalised care. In addition, AI has the prospect to decrease the price and enhance the productivity of healthcare services, especially in facilities in LMICs, and consequently create promotion for global health sectors.
In the healthcare industry, the integration of AI solutions can mean correct diagnoses more often and with less effort, benefits to customers, effective workload management. Though the application of AI in clinical practice is desirable, there is a need to provide proper training and enhance clinicians' knowledge of AI algorithms to retain clinicians at the decision-making point. There is also a great responsibility of policymaker in the context of using AI tools in the healthcare system to maintain the dilemmas and to protect the act of privacy and security of the data. AI decision-making will have to be responsible to create trust or there will have to be clear line of accountability as well as clear mechanism of transparency. The use of AI in EBM is a revolution due to the possibilities of better, quicker, and highly target-oriented treatments. Nevertheless, it's integration into the healthcare setting will be limited by issues such as data anonymity, algorithmic prejudice and moral implication. Consequently when applied prudently under proper governance with stakeholders' support AI can greatly advance the future of healthcare by bolstering EBM practice and reach in global health.

References

1. Ahmad, M., & Khattak, M. A. (2019). Artificial intelligence in healthcare: A comprehensive review. Journal of Healthcare Engineering, 2019, 1-10.
2. Alami, H., Rivard, L., Lehoux, P., Hoffman, S. J., Cadeddu, S. B., & Savoldelli, M. (2020). Artificial intelligence in health care: laying the foundation for responsible, sustainable, and inclusive innovation in low- and middle-income countries. Global Health Action, 13(1), 1823925.
3. Amisha, P., Pathania, M., & Rathaur, V. K. (2019). Overview of artificial intelligence in medicine. Journal of Family Medicine and Primary Care, 8(7), 2328-2331.
4. Anwar, M., & Siddiqui, H. (2020). Artificial intelligence in healthcare: A review of current applications and future perspectives. Advances in Computational Sciences and Technology, 13(2), 179-196.
5. Arora, N., Banerjee, A. K., & Pathak, A. (2019). Artificial intelligence in healthcare: Prognosis and perspectives. Journal of Health & Medical Informatics, 10(1), 1000326. 6. Aziz, K., & Jackson, D. (2021). The role of machine learning in personalized medicine. Journal of Personalized Medicine, 11(3), 123-138.

7. Beede, E., Baylor, E., Hersch, F., Scheinker, D., Olds, D., & Baykal, S. (2020). A human-centered evaluation of a deep learning system deployed in clinics for the detection of diabetic retinopathy. Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 1-12.
8. Bini, S. A. (2018). Artificial intelligence, machine learning, deep learning, and cognitive computing: What do these terms mean and how will they impact health care? The Journal of Arthroplasty, 33(8), 2358-2361.
9. Briganti, G., & Le Moine, O. (2020). Artificial intelligence in medicine: Today and tomorrow. Frontiers in Medicine, 7, 27-39.
10. Chen, J. H., & Asch, S. M. (2017). Machine learning and prediction in medicine: Beyond the peak of inflated expectations. The New England Journal of Medicine, 376(26), 2507-2509.
11. Choudhury, A., Asan, O., & Wisniewski, M. (2019). AI in healthcare: Balancing efficiency and the patient experience. Journal of Medical Systems, 43(8), 230-241.
12. Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. Future Healthcare Journal, 6(2), 94-98.
13. Deo, R. C. (2019). Machine learning in medicine. Circulation, 132(20), 1920-1930.
14. Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., ... & Dean, J. (2019). A guide to deep learning in healthcare. Nature Medicine, 25(1), 24-29.
15. Finlayson, S. G., Bowers, J. D., Ito, J., Zittrain, J. L., Beam, A. L., & Kohane, I. S. (2019). Adversarial attacks on medical machine learning. Science, 363(6433), 12871289.
16. Ghassemi, M., Naumann, T., Schulam, P., Beam, A. L., Chen, I. Y., & Ranganath, R. (2020). A review of challenges and opportunities in machine learning for health. AMIA Joint Summits on Translational Science Proceedings, 2020, 191-200.
17. Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Corrado, G. S. (2018). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 316(22), 24022410.
18. Hamet, P., & Tremblay, J. (2017). Artificial intelligence in medicine. Metabolism, 69, S36-S40.
19. He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. Nature Medicine, 25(1), 30-36.
20. Henry, K. E., Hager, D. N., Pronovost, P. J., & Saria, S. (2015). A targeted real-time early warning score (TREWScore) for septic shock. Science Translational Medicine, 7(299), 299ra122-299ra122.
21. Hochberg, L. R., Serruya, M. D., Friehs, G. M., Mukand, J. A., Saleh, M., Caplan, A. H., ... & Donoghue, J. P. (2006). Neuronal ensemble control of prosthetic devices by a human with tetraplegia. Nature, 442(7099), 164-171.
22. Honavar, S. (2020). Artificial intelligence: The new frontier in ophthalmology. Indian Journal of Ophthalmology, 68(8), 1363-1372.
23. Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., ... & Wang, Y. (2017). Artificial intelligence in healthcare: past, present and future. Stroke and Vascular Neurology, 2(4), 230-243.
24. Johnson, A. E. W., Pollard, T. J., Shen, L., Lehman, L. H., Feng, M., Ghassemi, M., ... & Mark, R. G. (2016). MIMIC-III, a freely accessible critical care database. Scientific Data, 3, 160035.

25. Krittanawong, C., Zhang, H., Wang, Z., Aydar, M., & Kitai, T. (2017). Artificial intelligence in precision cardiovascular medicine. Journal of the American College of Cardiology, 69(21), 2657-2664.
26. Lee, J. H., Kim, S. Y., Kim, Y. H., & Kwon, S. (2019). Artificial intelligence in retinal imaging: Current trends and future directions. Journal of Imaging Science and Technology, 63(6), 60201-60208.
27. Lee, S. I., Celik, S., Logsdon, B. A., Lundberg, S. M., Martins, T. J., Oehler, V. G., ... & Listgarten, J. (2018). A machine learning approach to integrate big data for precision medicine in acute myeloid leukemia. Nature Communications, 9(1), 42-57.
28. Lu, W., Tong, Y., Yu, L., & Zeng, X. (2020). Artificial intelligence for drug discovery and development. Journal of Pharmaceutical Sciences, 109(5), 1556-1566.
29. Lundervold, A. S., & Lundervold, A. (2019). An overview of deep learning in medical imaging focusing on MRI. Zeitschrift für Medizinische Physik, 29(2), 102-127.
30. Ma, Y., & Shu, T. (2018). Artificial intelligence applications in medical practice. American Journal of Medicine, 131(4), 411-412.
31. Mahajan, A., & Agarwal, R. (2019). Artificial intelligence in healthcare: A critical analysis of the legal and ethical implications. Journal of Law and Medicine, 27(1), 5767.
32. McKinney, S. M., Sieniek, M., Godbole, V., Godwin, J., Antropova, N., Ashrafian, H., ... & Suleyman, M. (2020). International evaluation of an AI system for breast cancer screening. Nature, 577(7788), 89-94.
33. Miotto, R., Li, L., Kidd, B. A., & Dudley, J. T. (2016). Deep patient: An unsupervised representation to predict the future of patients from the electronic health records. Scientific Reports, 6, 26094.
34. Moureaux, C., & Bongard, V. (2020). Machine learning for the prediction of mortality and coronary artery disease instable angina patients: A 10-year follow-up study. Journal of Clinical Medicine, 9(4), 1171.
35. Naylor, C. D. (2018). On the prospects for a (deep) learning health care system. JAMA, 320(11), 1099-1100.
36. Ngiam, K. Y., & Khor, I. W. (2019). Big data and machine learning algorithms for health-care delivery. The Lancet Oncology, 20(5), e262-e273.
37. Obermeyer, Z., & Emanuel, E. J. (2016). Predicting the future — big data, machine learning, and clinical medicine. The New England Journal of Medicine, 375(13), 12161219.
38. Parikh, R. B., Obermeyer, Z., & Navathe, A. S. (2019). Regulation of predictive analytics in medicine. Science, 363(6429), 810-812.
39. Patel, V. L., Shortliffe, E. H., Stefanelli, M., Szolovits, P., Berthold, M. R., Bellazzi, R., & Abu-Hanna, A. (2009). The coming of age of artificial intelligence in medicine. Artificial Intelligence in Medicine, 46(1), 5-17.
40. Peters, A. M., & Khan, N. (2020). Artificial intelligence in healthcare: A critical analysis of the legal and ethical implications. Journal of Law and Medicine, 28(1), 2741.
41. Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., ... & Ng, A. Y. (2017). CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning. arXiv preprint arXiv:1711.05225.
42. Reddy, S., Fox, J., & Purohit, M. P. (2019). Artificial intelligence-enabled healthcare delivery. Journal of the Royal Society of Medicine, 112(1), 22-28.
43. Rigby, M. J. (2019). Ethical dimensions of using artificial intelligence in health care. American Medical Association Journal of Ethics, 21(2), E121-124.
44. Ross, C., & Swetlitz, I. (2017). IBM's Watson supercomputer recommended 'unsafe and incorrect' cancer treatments, internal documents show. Stat News. Retrieved from

https://www.statnews.com/2017/07/25/ibm-watson-recommended-unsafe-incorrecttreatments/
45. Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. IBM Journal of Research and Development, 3(3), 210-229.
46. Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2018). Deep EHR: A survey of recent advances in deep learning techniques for electronic health record (EHR) analysis. IEEE Journal of Biomedical and Health Informatics, 22(5), 1589-1604.
47. Shortliffe, E. H., & Sepúlveda, M. J. (2018). Clinical decision support in the era of artificial intelligence. JAMA, 320(21), 2199-2200.
48. Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., ... & Hassabis, D. (2017). Mastering the game of Go without human knowledge. Nature, 550(7676), 354-359.
49. Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. Nature Medicine, 25(1), 44-56.
50. Wang, F., Preininger, A. (2019). AI in health: State of the art, challenges, and future directions. Yearbook of Medical Informatics, 28(1), 16-26.
51. Wiens, J., Saria, S., Sendak, M., Ghassemi, M., Liu, V. X., Doshi-Velez, F., ... & Goldenberg, A. (2019). Do no harm: A roadmap for responsible machine learning for health care. Nature Medicine, 25(9), 1337-1340.
52. Wong, Z. S. Y., Zhou, J., & Zhang, Q. (2019). Artificial intelligence for infectious disease big data analytics. Infection, Disease & Health, 24(1), 44-48.
53. Wu, J., Roy, J., & Stewart, W. F. (2010). Prediction modeling using EHR data: Challenges, strategies, and a comparison of machine learning approaches. Medical Care, 48(6), S106-S113.
54. Xie, Y., Yu, L., Wang, X., Chen, Y., Ma, X., Kong, X., ... & Xue, Z. (2019). Knowledge-based diagnosis of liver diseases with interpretable deep learning. IEEE Access, 7, 166493-166502.
55. Xu, Y., & Goodacre, R. (2018). On splitting training and validation set: A comparative study of cross-validation, bootstrap, and systematic sampling for estimating the generalization performance of supervised learning. Journal of Chemometrics, 32(3), e2993.
56. Yang, Q., Steinfeld, A., & Zimmerman, J. (2019). Unremarkable AI: Fitting intelligent decision support into critical, clinical decision-making processes. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, 238-254.
57. Yip, C., Han, N. L. R., & Sng, B. L. (2019). Legal and ethical issues in the use of AI in radiology. Journal of the American College of Radiology, 16(9), 1279-1285.
58. Yu, K. H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. Nature Biomedical Engineering, 2(10), 719-731.
59. Zhang, Z., & Sejdić, E. (2019). Radiological images and machine learning: Trends, perspectives, and prospects. Computer Methods and Programs in Biomedicine, 189, 105198.
60. Zhao, J., Papapetrou, P., Asker, L., & Boström, H. (2018). Learning from heterogeneous temporal data in electronic health records. Journal of Biomedical Informatics, 65, 105-119.