Review Article

Leveraging AI to enhance electronic health records

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Article Info

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Keywords

artificial intelligence, electronic health record, healthcare, medicine

Abstract

The artificial intelligence (AI) integration in the medical field benefits both clinicians and patients. One of the most exciting applications of AI in healthcare is its role in electronic health records (EHRs). Leveraging AI to enhance EHR holds incredible potential for streamlining processes and reducing errors, enhancing clinical decision support and improving interoperability, contributing to more accurate, personalized, and effective healthcare, improved patient outcomes and quality of life. This article provides an overview of the role of AI in EHR, illustrates several examples of how AI incorporation into EHRs transforms healthcare delivery, illustrates how AI-powered EHRs impact healthcare stakeholders, and highlights the challenges and barriers of AI adoption in EHR systems.

Introduction

Electronic Health Record (EHR), essential part of modern healthcare systems, is comprehensive digitalized patient-centred record, that gives information instantly and securely to multiple healthcare care providers and healthcare organizations. EHRs contain a wide variety of data types. The main types of EHRs data that AI can analyse could be classified in: structured, semi-structured and unstructured data. Structured data are well-organized, easily quantifiable, often stored in predefined format and structure. They include demographics (age, gender, ethnicity, address, insurance status), as well as weight/height, heart rate, blood pressure, blood group, laboratory test results, medication records (current prescriptions, dosage, timing, history of use), diagnoses and codes, procedure codes, immunization records (vaccination type, dates), allergies, metadata, and information related to generation of data. Semi-structured data are more flexible compared with structured data, mainly as a text describing smoking status, chronic disease, examination results, etc. Unstructured data, the most detailed form of data, lacks a defined structure, and includes clinical notes, surgical notes, radiology reports, audio, and video recordings [1, 2].

The history of EHRs is a story of gradual adoption over the last sixty years, accompanied by significant technological, financial, and policy-driven changes. EHRs have evolved significantly from simple data sources to integral components of the healthcare system, offering a lot of opportunities to enhance collaborative care, promote patient active engagement in their health management, and facilitate clinical research [3,4]. The projected global EHR market is $93 billion by 2035, with compound annual growth rate of 8.6% from 2024 to 2035. Growth is a consequence of increased adoption of EHR systems, rising demand for efficient healthcare data management, and integration of technologies [5]. The combination of AI with the wealth of data stored in EHR redefines its role, enabling greater benefits from digital records to improve diagnostic accuracy, reshape patient care strategies, support clinical decision-making to streamline operations, and enhance healthcare outcomes across various medical fields.

Role of AI in EHRs

Leveraging AI in EHRs improves it in different segments [6-10]

- Data entry: AI can automatically enter data into EHR by extracting information from scanned documents, clinical notes, voice recordings, saving time, reducing manual effort, and improving quality of patients' records, reducing errors.
- Data organization: AI can help sort and organize data efficiently. It can categorize patient information, making it easier to access specific details (lab results, prescriptions, or medical histories), prioritize urgent tasks.
- Virtual medical assistant is able to send reminders, answer simple patient questions.
- Automating billing/coding: AI can automatically identify the correct codes based on clinical notes and test results, reducing human error and speeding up reimbursements.
- Claims management: AI can also help in managing insurance claims by analysing patterns in rejected claims and helping healthcare providers to take proactive steps to avoid claim denials.
- Data Analysis: AI models can analyse large volumes of EHR data, and can identify patterns and trends in patient data that are not immediately obvious to clinicians and help in patient's diagnosis and management.
- Predictive Analytics: AI models can analyse EHRs historical data and risk factors, with the aim to predict a patient's likelihood of developing some disease/outcome, prioritizing the decision on the appropriate management
- Natural language processing (NLP) helps extract valuable insights from unstructured data in EHRs, such as physician notes, discharge summaries, and patient narratives; assist with the automation of medical coding by interpreting physician notes and accurately applying ICD-10 codes; Improve the accuracy of clinical documentation by identifying missing information and suggesting relevant additions or corrections.
- Automated Image and Signal Analysis: AI-driven EHRs can help in analysis of X-rays, MRIs, or CT scans, ECGs
- Clinical Decision Support: AI-powered EHRs can issue clinicians with real-time evidence-based recommendations, assist in diagnosis, provide tailored recommendations and treatment plans, analysing patient data (medical history, genetics, lifestyle factors), flag potential drug interactions, adverse drug reactions.
- Personalized Medicine: AI-driven EHR analyse clinical, genomic, proteomic data to give accurate diagnosis, optimize treatment strategies, predict drug responses, with the aim to reduce adverse reactions, improve patient outcomes personalizing care for every individual.
- Reducing Healthcare Costs: AI/EHR integration can help reduce costs by reducing readmission rates (AI can predict readmission risks based on EHR data, allowing healthcare providers to take preventive action) and optimizing resource allocation (AI can help identify underused resources, optimize staffing, and streamline hospital workflows based on patient data).

AI can help manage and streamline EHRs by automating administrative tasks and improving administrative efficiency. Streamlining administrative tasks, actually reducing healthcare workers′ burnout induced by increased administrative burden, "computer fatigue" and stress, EHRs that are not user/friendly, lack of adequate training, disruptions in patient-provider interaction, increase in workload outside of office hours, cognitive load and multitasking (interacting with patients, managing EHRs, reviewing laboratory results, etc.).

Application of AI in EHRs

The application of AI in EHR requires four steps that are important in preparing data for processing with AI [11]:

- Data collection -AI for extracting data from different healthcare providers
- Data cleaning - AI corrects errors (missing values, removes duplicates, fix inconsistencies)
- Normalisation and standardisation- AI models normalize and standardize quantitative data with the aim to adjust data to a standard scale for the purpose of comparability
- Data preservation- AI helps monitor and secure data throughout the process with the aim to enable data integrity/confidentiality.

AI-powered EHR impact on healthcare stakeholders

The impact of AI-powered EHRs spans across a variety of stakeholders (patients, healthcare providers, administrators, insurers, and policymakers). Here's a breakdown of how each is affected [12]:

- Patients benefit from improved diagnosis and treatment, faster service, reduced errors, better engagement
- Healthcare professionals' benefits from reducing administrative burden, clinical decision support, workflow optimisation
- Hospital/Clinic Administrators- benefits from improvement in operational efficiency, financial performances, quality metrics
- Developers of EHR Software - responsibility for creating systems, development, maintenance, and utilisation in clinical practice, compliance with regulative.

Integration of AI to EHR-based models: real-word implementation

There are several real-world examples of how AI is integrated with EHRs, specifically in cardiology field during last few years.

Recent evidence showed that AI tools applied to EHR data analysis enhanced accurate cardiovascular risk assessments, enable earlier interventions and personalized patients′ management, but also have implications for clinical trial design. It seems that AI models offer superior results compared with traditional risk algorithms for prediction of atherosclerotic cardiovascular disease risk, and overperformed cardiology trainees in the correct interpretation of ECG abnormalities. Literature data shows that coronary artery disease (CAD) prediction score using EHR clinical features (EHR score) predict CAD risk one year prior to diagnosis in health system [13]. Wu et al. [14] discovered the potential of natural language processing to improve the detection and diagnosis of heart failure (HF) with preserved ejection fraction patients from unstructured EHR data. It is very important because this is the predominant form of HF that is still underdiagnosed in clinical environment and connected with elevated mortality.

Using deep neural network, Raghunath et al. [15] created AI model that can predict one-year all-cause mortality from large subset of ECG voltage–time traces, even in patients whose ECG was interpreted as normal. Further, they discovered that a deep neural network could predict new-onset AF in patients without a history of atrial fibrillation, from the resting 12-lead ECG, and that this prediction may help identify those at risk of atrial fibrillation-related stroke and prevent it [16]. A novel machine learning platform that uses 12-lead electrocardiogram data, age and sex was developed to identify patients with high risk of undiagnosed structural heart disease with excellent performance, i.e., any one of seven structural heart diseases that are diagnosable by echocardiography [17]. The first report on using machine learning and EHR data to predict EF changes across a large cohort of HF patients from three academic medical centers was recently published [18]. It was shown that EHR-based deep learning model can assist clinicians in early identification patients with HF who are at risk of severe decompensation or death, and help in decision about advanced HF surgical interventions [19].

Yang et al. [20] showed that AI based on EHRs can be useful for cancer care in neoplasm categorization, methods/algorithms, application in cancer care, and data/data sets. NLP has shown significant potential in cancer research using EHRs and clinical notes, especially in breast, lung, and colorectal cancers [21]. Integration of AI with EHRs, can contribute to the quick and precise recruitment of patients in clinical trial (monitoring patients' data and determine eligibility), that can influence the effectiveness of clinical trials and receiving new cancer therapies [22].

Sarwal et al. [23] developed NLP algorithm that with high sensitivity automatically identify familial and genetic risk of pancreatic cancer from unstructured clinical notes within the EHR, that can contribute. This algorithm is the first step in identification high-risk patients who will benefit from risk-based PC screening in early, asymptomatic stage that can positively impact survival rates. Li et al. [24] established the first deep learning application to predict brain metastases in lung cancer patients diagnosed on the basis of EHR data. Last month, a new machine learning model developed to enhance prostate cancer screening by predicting the likelihood of an abnormal prostate MRI using EHR, was announced. The model analyses factors from EHR including age, prostate-specific antigen levels, prostate size (volume), and body mass index. At the same time, this model can potentially optimize the MRI utilization, potentially reducing wait times and minimizing unnecessary biopsies [25].

One of the newest applications of AI is in cardio-oncology, focused on the identification of patients at high risk for cardiovascular problems during cancer treatment who need timely to refer to cardio-oncologists and expand access to appropriate cardiovascular care. Using a large dataset of deidentified EHRs of patients with breast, kidney, B-cell lymphoma cancers and patients who receive immunotherapy,

Al-Droubi et al. [26] trained/tested the machine learning model to identify oncology patients who are at risk for cardiovascular problems during cancer treatment.
Machine learning models that use EHRs' clinical data can predict the risk of sepsis before the onset of symptoms, in early detection, diagnosis, subtyping analysis, prognosis assessment, and management of treatment [27,28]. The observational study that included non-ICU patients revealed that a machine learning causal probabilistic network algorithm model can predict sepsis within 48 hours using EHR data [29] . Nemati et al. [30] constructed a deep learning model to predict sepsis 4 hours in advance using EHR data together with high-resolution time series dynamics of heart rate and blood pressure.
In the past couple of years, studies about rare diseases and AI have the potential to significantly enhance the management of rare diseases by improving early and more accurate detection, personalizing treatment, optimizing care, predicting the progression of the disease and supporting clinical research. The integration of AI into EHR systems offers a comprehensive approach to managing these complex, multi-system disorders, ultimately improving patient outcomes and quality of life.
As EHRs are wide, precious source of information it can be used to develop and evaluate ML-based screening and NLP methods to identify rare diseases. Phenotypes and clinical signs are extracted from EHRs, and obtained data are processed to calculate phenotypic distances. Rare disease expert physicians decide whether or not to perform complementary tests to confirm the diagnosis. The rapid redirection of patients to rare disease experts via chatbots, and consultations via telemedicine should ensure faster management. The emergence of large language models opens new perspectives for the reuse of textual data that are still unexplored [31].
About fourteen EHR-based familial hypercholesterolemia screening algorithms and/or tools have described to enhance identification of familial hypercholesterolemia. Although there is no sufficient evidence supporting the use of this algorithms/tools, they show the potential for improving population-level detection and management of patients with familial hypercholesterolemia [32].

Challenges and barriers to AI adoption in EHR
While the integration of EHRs and AI offers many benefits, there are still several challenges ranging from technical to organizational issues [11]:

- Data Privacy and Security: EHRs contain sensitive patient information, and patients′ data should always be protected according to the regulations like HIPPA and GDPR.
- Interoperability: Integration with existing systems often requires substantial technical upgrades which are expensive and time-consuming;
- Bias in AI models: In the case the AI model is trained on incomplete or non-representative dataset, it can influence the effectiveness of AI algorithms, and influence clinical decisions;
- Workforce trust, training and adaptation-Healthcare workers must be adequately trained on user-friendly interfaces and convinced that AI is a helpful tool rather than a replacement, which may require overcoming resistance to change. demystify the processes behind AI applications and build a foundation of trust and confidence.

Conclusion
The use of artificial intelligence is shaping electronic health records, paving the way for improved clinical practice and better patient outcomes.

Data Availability Statement
Data will be provided on request.

Declaration of conflict of interest
The author of this article declares that there is no conflict of interest with regard to the content of this manuscript.

Funding
None.

Submission declaration
The work described has not been published previously in this form. The article is not under consideration for publication elsewhere.

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