Generative AI Empowering Clinical Decision-Making: A Review of Research from Medical Record Analysis to Treatment Optimization

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Abstract

This review explores generative AI's role in empowering clinical decision-making, covering its applications, challenges, and future directions. In medical record analysis, generative AI—via NLP—extracts key data from unstructured text (e.g., TNM stages from radiology reports, SMI symptoms from discharge summaries) and generates synthetic, de-identified notes for privacy-preserving research, while also synthesizing patient timelines and clinician-friendly summaries. For diagnosis and prognosis, it creates synthetic medical images (e.g., CMR via GANs) to augment limited datasets, predicts disease progression (e.g., CKD's need for RRT) and severity, enables early detection, and generates differential diagnoses (e.g., GPT-4's 98.21 F1-score for anemia subtypes). In personalized care and drug discovery, it predicts treatment responses (e.g., 73.52% accuracy for pulmonary fibrosis corticotherapy), designs tailored plans, accelerates drug development (e.g., de novo molecule design), and forecasts drug-drug interactions (e.g., via MKGFENN). Key challenges include data privacy (addressed via encryption/synthetic data), bias mitigation (to avoid care disparities), ensuring AI reliability (aided by 32-item evaluation checklists), and ethical concerns (preventing clinician over-reliance). Future directions involve integrating generative AI with RL for adaptive care, developing explainable models, and expanding to mental health (e.g., schizophrenia prognosis) and public health. Generative AI holds great promise for more efficient, equitable healthcare.

Key words: artificial intelligence； clinical decision； treatment optimization； medical diagnosis

Introduction

Generative Artificial Intelligence (AI) is rapidly transforming various sectors, and healthcare is no exception. Its potential to revolutionize clinical decision-making is particularly promising, offering opportunities to enhance efficiency, accuracy, and personalization of patient care. Clinical decision-making, a complex process involving the synthesis of patient data, medical knowledge, and clinical experience, faces numerous challenges, including information overload, cognitive biases, and the increasing complexity of medical knowledge. Generative AI, with its ability to learn complex patterns from vast datasets and generate novel content, offers a powerful tool to address these challenges and improve clinical outcomes. This review explores the current landscape of research on generative AI in clinical decision-making, spanning from medical record analysis to treatment optimization.

This review is structured to provide a comprehensive overview of the field. We begin by examining the application of generative AI in medical record analysis and information extraction, focusing on how techniques like Natural Language Processing (NLP) are used to extract key information from unstructured clinical text, de-identify patient data, synthesize patient timelines, and generate medical summaries. This section highlights the crucial role of generative AI in organizing and streamlining the wealth of information contained within medical records. Next, we delve into the use of generative AI in disease diagnosis and prognosis prediction, exploring how generative models can create synthetic medical images, predict disease progression, enable early disease detection, and generate differential diagnoses. This demonstrates the potential of generative AI to improve the accuracy and speed of diagnostic processes. The review then shifts its focus to personalized treatment recommendations and drug discovery, examining how generative AI can predict patient response to treatment, design personalized treatment plans, discover novel drug candidates, and predict drug-drug interactions. This section underscores the promise of generative AI in tailoring treatment strategies to individual patient needs. Subsequently, we address the challenges and limitations of generative AI in clinical decision-making, including data privacy concerns, bias mitigation, ensuring reliability, and addressing ethical implications. This critical discussion highlights the need for careful consideration and responsible implementation of these technologies. Finally, we conclude by outlining future directions and potential advancements in the field, including the integration of generative AI with other AI techniques, the development of explainable AI models, and the expansion of its application to new areas of healthcare. By exploring these diverse facets, this review aims to provide a comprehensive understanding of the current state and future potential of generative AI in empowering clinical decision-making.

Generative AI for Medical Record Analysis and Information Extraction

The analysis and extraction of information from medical records stand as a crucial application of generative AI in healthcare, with the potential to revolutionize clinical decision-making. This encompasses a range of techniques, from processing unstructured text to synthesizing comprehensive patient timelines and generating summaries for clinicians.

Natural Language Processing (NLP) techniques are fundamental to unlocking the wealth of information contained within unstructured clinical text, such as progress notes and discharge summaries [1, 2]. By structuring free text, NLP enables a deeper understanding of patient data. In radiology, for instance, accurate and complete reports are essential for clinical staging, and NLP can automatically extract key elements like the T and N stage of the tumor-node-metastasis (TNM) classification system from radiological reports, aiding in pulmonary oncology staging [1]. The broad applicability of NLP is further demonstrated by its use in extracting severe mental illness (SMI) symptoms from discharge summaries, achieving high accuracy [2], and in identifying information within epilepsy clinic letters [3] and basal cell carcinoma (BCC) histopathology reports [4]. These successes highlight NLP's potential to enhance routinely collected data for research and improve the quality of cancer registries [4, 17]. However, the effectiveness of NLP algorithms remains contingent on the quality of the input text, vocabulary, and contextual understanding, especially when dealing with uncertainty [1].

Beyond information extraction, generative models are being investigated for their ability to de-identify patient data while preserving its clinical utility [5]. The aim is to create synthetic clinical notes that can be shared openly without compromising patient privacy. By training generative models on real, de-identified records, researchers are exploring the possibility of automatically generating synthetic clinical notes [5]. The utility of these synthetic notes is then assessed by measuring their performance in training clinical NLP models [5]. While promising results have been achieved, further improvements are needed to ensure the utility of synthetic notes closely matches that of real notes in various clinical NLP tasks [5]. Although automatic de-identification techniques can introduce noise into the data, studies suggest that this noise may not significantly harm the utility of clinical data for NLP tasks [6].

Addressing the challenge of fragmented medical records, generative AI offers the potential to synthesize comprehensive patient timelines [7]. By integrating information from disparate sources, such as progress notes, lab results, and imaging reports, these models can create a unified view of a patient's medical history. This capability can significantly improve clinical decision-making by providing clinicians with a more complete and accessible understanding of a patient's health trajectory. Generative AI can automatically identify relevant events, arrange them chronologically, and highlight potential relationships and patterns that might otherwise be missed. Furthermore, generative AI can identify gaps in the medical record and suggest potential areas for further investigation, ultimately leading to more informed and proactive patient care [7].

Finally, generative AI is being explored for its ability to automatically generate medical summaries for clinicians, potentially improving efficiency and report quality [8]. AI-generated radiology reports, including summary reports and patient-friendly reports, have received high scores in qualitative and quantitative assessments [8]. Notably, patient-friendly reports generated by AI have demonstrated improved patient understanding compared to original reports [8]. While these models hold promise, it's important to acknowledge their limitations, such as the potential for artificial hallucinations and potentially harmful translations [8].

Generative AI in Disease Diagnosis and Prognosis Prediction

Generative AI is rapidly transforming disease diagnosis and prognosis prediction, offering innovative solutions across various clinical applications. One significant area is the use of generative models to address the challenge of limited medical imaging data. These models, including Generative Adversarial Networks (GANs) and diffusion models, are being explored for their capacity to create synthetic medical images, augmenting training datasets for diagnostic AI systems [33, 35]. By generating realistic medical images, these models can enhance the performance and robustness of deep learning models used in diagnosis [21, 32, 35]. For instance, a GAN-based approach developed by Ahmadi Golilarz et al. successfully generated synthetic cardiac magnetic resonance (CMR) images for myocarditis diagnosis, effectively tackling imbalanced classification issues and achieving superior results [9]. Similarly, a specialized GAN architecture proposed by Dhawan et al. generated synthetic chest X-ray data representing healthy lungs and various pneumonia conditions. Training an EfficientNet v2 model with both real and synthetic data resulted in high accuracy in brain MRI classification, showcasing the potential of this approach [10]. While diffusion models have demonstrated promise in generating high-quality skin images for training dataset augmentation [11], Schaudt et al. observed that GAN-based methods outperformed diffusion-based methods in generating chest X-ray images for pneumonia diagnosis within a limited dataset [12]. This highlights the importance of carefully selecting the generative model based on the specific application and dataset characteristics. Interestingly, their research also revealed that improved image quality did not always translate to enhanced classification performance, suggesting careful consideration is needed when utilizing generative models for limited data scenarios [12]. These collective findings underscore the potential of synthetic data augmentation in improving disease classification accuracy across diverse pathological conditions [10].

Beyond image analysis, generative AI is also being leveraged to predict disease progression by analyzing patient history and clinical data [13]. These models excel at identifying patterns and risk factors that may not be readily apparent to clinicians, leading to earlier and more accurate prognoses. The work of Isaza-Ruget et al. exemplifies this, with their development and validation of a machine learning-based model to predict the need for renal replacement therapy (RRT) and disease progression in patients with stage 3–5 chronic kidney disease (CKD) [13]. Their time-to-event model demonstrated strong performance in predicting three outcomes of CKD progression at five years, highlighting the potential of such models in clinical settings [13]. Furthermore, generative AI can assist in predicting disease severity. Li et al. discovered that consolidation volume quantified on initial chest CT was the strongest predictor for COVID-19 disease severity progression [14]. Their AI-based quantification of ground glass opacity (GGO) and consolidation volume revealed that a larger consolidation volume was associated with unfavorable clinical outcomes [14]. These examples demonstrate how generative AI can effectively utilize complex datasets to forecast disease trajectories and inform clinical decision-making.

The capacity of generative AI to identify subtle patterns within medical records also positions it as a valuable tool for the early detection of diseases, potentially uncovering insights that might be missed by human clinicians [15]. By analyzing vast amounts of patient data, including electronic health records (EHRs), laboratory results, and imaging studies, generative models can uncover correlations and anomalies indicative of early disease onset [23, 29]. AI-powered imaging analysis can rapidly screen large populations for signs of chronic diseases, flagging suspicious cases for further review by medical professionals [15]. Moreover, in the context of neurodegenerative diseases, Syndrome-dependent Pattern Recognition Method can be employed for the early detection and progression monitoring of these conditions [16].

Another promising application lies in generating differential diagnoses based on patient symptoms and medical history. These models can analyze complex datasets to suggest a range of possible conditions, aiding in the diagnostic process and potentially improving diagnostic accuracy. In a study evaluating Large Language Models (LLMs) for diagnosing anemia subtypes, Elisa Castagnari et al. found that GPT-4 achieved an impressive F1 score of 98.21, generating diagnostic pathways closely aligned with existing clinical guidelines [17]. This illustrates the potential of LLMs to assist in clinical pathway discovery from patient data [17]. Furthermore, the diagnostic performance of generative AIs using LLMs has been assessed across various medical specialties. Takanobu Hirosawa et al. analyzed case reports and found that ChatGPT-4 exhibited higher diagnostic accuracy compared to Google Gemini and LLaMA2 in generating differential diagnosis lists [18]. Specifically, ChatGPT-4 included the final diagnosis within its top 10 differential diagnoses in 86.7% of cases, underscoring the importance of understanding the performance differences among various generative AI platforms [18].

Generative AI for Personalized Treatment Recommendations and Drug Discovery

Generative AI is poised to revolutionize clinical decision-making through personalized treatment recommendations and accelerated drug discovery. Its capacity to analyze complex datasets and generate novel solutions offers unprecedented opportunities for improving patient outcomes and streamlining pharmaceutical development.

A key application lies in predicting patient response to different treatment options based on individual characteristics. This is particularly crucial in diseases exhibiting heterogeneous responses, such as lung cancer, where precision medicine approaches are paramount [19]. By integrating diverse patient data, including tumor molecular profiles, clinical history, and other salient factors, generative AI can facilitate more informed clinical decisions and the delivery of tailored therapies [41, 53]. Studies have demonstrated the potential of machine learning algorithms to predict treatment efficacy. For instance, models incorporating Decision Tree, Random Forest, and AdaBoost algorithms have shown promising results in predicting the benefit of corticotherapy for patients with pulmonary fibrosis, achieving balanced accuracy rates of up to 73.52% [20]. Such predictive capabilities empower clinicians to move beyond standardized protocols and optimize treatment strategies for individual patients.

Building upon this predictive power, generative AI can be leveraged to design personalized treatment plans that consider individual patient needs and preferences. By analyzing comprehensive patient data, encompassing medical history, lifestyle factors, and even genetic information, generative models can simulate potential treatment outcomes. This allows clinicians to identify the most effective and acceptable options for each patient, moving beyond a one-size-fits-all approach to care. This capability promises to enhance patient adherence and improve overall treatment success by aligning interventions with individual circumstances and preferences.

Beyond personalized treatment strategies, generative AI is transforming drug discovery by enabling the design of novel drug candidates and the optimization of drug formulations [21]. Traditional drug discovery is a resource-intensive and protracted process, with estimates suggesting costs of around $2.5 billion to bring a new drug to market [21]. Generative AI offers a pathway to accelerate this process by generating novel molecules with desired properties [46, 44]. These models can be employed for de novo drug design, creating molecules from scratch, or for fine-tuning existing molecules to enhance their pharmacokinetic and pharmacodynamic profiles [21]. Generative AI is being utilized in molecular property prediction, molecule generation, virtual screening, synthesis planning, and even drug repurposing [21]. Furthermore, AI algorithms are being incorporated into platforms like FormulationAI, a web-based tool that predicts and evaluates crucial properties of drug formulations, thereby streamlining the formulation design process by leveraging basic information on drugs and excipients [22]. The technology also extends to the design and discovery of novel peptides for therapeutic applications, addressing challenges associated with their short half-life and limited bioavailability [23].

Moreover, the application of generative AI extends to predicting drug-drug interactions (DDIs) and potential adverse effects, a vital aspect of ensuring patient safety and optimizing drug development [47, 49]. Traditional methods for identifying DDIs are often laborious and lack scalability, often failing to capture the intricate relationships between various drugs [24]. To overcome these limitations, researchers are exploring AI and machine learning techniques to develop more accurate and automated prediction methods [24]. For example, the Multimodal Knowledge Graph Fused End-to-end Neural Network (MKGFENN) has been proposed to predict DDI events by comprehensively exploiting DDI events-associated relationships and mechanisms from knowledge graphs encompassing drugs-chemical entities, drug-substructures, drugs-drugs, and molecular structures [25]. Furthermore, models combining drug similarity calculators and DDI predictors are being developed to process data in a "human-like" manner and predict interactions for newly developed drugs, achieving high accuracy rates [24].

Challenges and Limitations of Generative AI in Clinical Decision-Making

A significant hurdle in leveraging generative AI for clinical decision-making lies in addressing data privacy and security concerns, especially given the sensitive nature of patient information [26]. While generative AI models offer substantial capabilities, their deployment necessitates careful consideration of potential protected health information exposure [26]. Yan Chen et al. underscore the novel threats to protected health information posed by data-intensive generative AI systems [26]. To mitigate these risks, robust encryption and decryption protocols are essential, as highlighted by Pi-Yun Chen et al. for ensuring the infosecurity of biosignals and medical images within IoMTS [27]. Furthermore, innovative techniques such as synthetic data generation, exemplified by Jan-Niklas Eckardt et al.'s work using CTAB-GAN+ and normalizing flows, present a promising strategy for circumventing privacy issues. By generating realistic yet non-identifiable patient data, these methods facilitate research and model training without compromising patient confidentiality [28].

Beyond data security, mitigating bias in generative AI models is paramount to ensuring fairness and equity in clinical decision-making [29]. AI systems, including generative models, can inadvertently perpetuate and amplify existing societal inequalities if not carefully managed [29]. This is particularly worrisome in healthcare, where biased AI can lead to disparities in diagnosis, treatment strategies, and patient outcomes [30]. Drukker et al. have identified various sources of bias in AI/ML development for medical imaging, spanning from data collection to model deployment [31]. The potential for biased AI to influence clinical judgment is further illustrated by Adam et al.'s findings, which demonstrate that both clinicians and non-experts can be swayed by prescriptive recommendations from biased AI in emergency mental health scenarios, leading to skewed decisions [32]. Interestingly, framing AI advice as descriptive flags rather than prescriptive directives can mitigate this effect, enabling decision-makers to maintain their original, unbiased judgment [32]. Consequently, addressing bias necessitates a comprehensive approach encompassing diverse and representative datasets, transparency, accountability mechanisms, and rigorous ethical considerations [57, 64].

The reliability and trustworthiness of generative AI outputs represent another critical challenge for its successful integration into clinical settings. Clinicians' perceptions of generative AI's impact vary, particularly concerning its trustworthiness and the potential for introducing bias [33]. In response to these concerns, Chen et al. have developed a comprehensive 32-item checklist for evaluating generative AI performance in medical contexts [34]. This checklist encompasses crucial aspects such as question collection, querying methodologies, and assessment techniques, providing a standardized and systematic approach for evaluating generative AI's suitability for medical applications. By guiding researchers through potential challenges and pitfalls, this framework aims to enhance research quality and reporting, ultimately fostering greater confidence in generative AI's reliability [34].

Finally, the ethical implications of employing generative AI to automate clinical decision-making processes demand careful consideration. A primary concern revolves around the potential for bias in AI models, which can lead to unfair or inequitable clinical decisions [35]. Generative AI has the potential to replicate existing biases in the decision-making process, raising concerns about justice [35]. The inherent "black box" nature of some generative AI models also raises concerns about transparency and accountability. If clinicians lack understanding of how a model arrives at a specific recommendation, it becomes challenging to assess its validity or justify it to patients. Lahat et al. acknowledge the promising potential of ChatGPT to assist physicians with medical issues, enhancing diagnostics, treatments, and ethical considerations [36]. However, they also emphasize that its integration into clinical workflows should complement, not replace, human expertise [36]. This underscores the critical need for careful deliberation on how generative AI is implemented in clinical settings to ensure that it augments, rather than diminishes, human judgment and ethical considerations.

Future Directions and Potential Advancements

The trajectory of generative AI in clinical decision support points toward a future characterized by synergistic integrations and expanded applications. One prominent avenue involves the fusion of generative AI with other artificial intelligence techniques, such as reinforcement learning (RL), to cultivate more adaptive and personalized clinical support systems. RL offers a mechanism for optimizing treatment strategies by iteratively learning from the outcomes of generative AI-driven recommendations, thereby accommodating the unique responses of individual patients over time [37]. The study by Prasad et al. serves as a compelling illustration, demonstrating how RL-driven electrolyte repletion recommendations can significantly reduce the frequency of magnesium and potassium replacements (up to 60%), refine the timing of interventions, and promote the use of orally administered repletion, ultimately enhancing safety and cost-effectiveness [37]. This symbiotic relationship establishes a continuous feedback loop wherein generative AI proposes potential solutions, and RL progressively refines these suggestions based on real-world results, culminating in more effective and precisely tailored clinical interventions.

However, the realization of generative AI's full potential in clinical settings hinges on the development of explainable models, which are crucial for cultivating trust and facilitating a deeper understanding of clinical decision-making [38]. Despite the powerful capabilities offered by generative AI, its inherent "black box" nature can impede its adoption in healthcare, where transparency is of paramount importance. Maurer et al. underscore the urgent need for explainable AI (XAI) methods to address this challenge, particularly in the context of deep learning applications within healthcare [38]. XAI techniques offer the means to illuminate the decision-making processes of these models, enabling clinicians to comprehend the rationale behind a particular diagnosis or treatment recommendation. Visualizing relevance attributions on biosignals, such as ECGs and EEGs, can provide valuable insights into how the AI arrived at a specific prediction [38]. It is important to note the findings of Glick et al., which indicated that dental students using AI assistance to detect furcation involvement in radiographs exhibited a tendency towards over-reliance on AI. This highlights the importance of caution to avoid over-dependence on AI-generated information [39]. Therefore, alongside the development of explainable models, strategies to mitigate over-reliance and promote critical evaluation of AI outputs are essential.

Beyond traditional clinical settings, generative AI is poised to revolutionize other areas of healthcare, with mental health and public health emerging as promising frontiers. In mental healthcare, Large Language Models (LLMs) have demonstrated the potential to assist in assessing the prognosis of schizophrenia, with some models exhibiting predictions that align closely with those of mental health professionals [40]. Concurrently, public interest in AI applications for mental health is on the rise, with Google Trends data projecting a 114% increase in interest through the end of 2024, signifying growing awareness and acceptance of AI in this domain [41]. Nevertheless, it is crucial to acknowledge that some LLMs may exhibit biases or provide substandard information, necessitating careful human oversight and validation when used for mental health education or direct-consumer queries [42]. As generative AI expands its reach into these sensitive domains, rigorous validation, bias mitigation, and ethical considerations must remain central to its development and deployment.

Conclusion

In summary, this review highlights the transformative potential of generative AI in empowering clinical decision-making, spanning from streamlining medical record analysis and enhancing diagnostic accuracy to personalizing treatment recommendations and accelerating drug discovery. The landscape is rapidly evolving, with ongoing research focused on addressing critical challenges such as data privacy, bias mitigation, and ensuring the reliability and trustworthiness of AI-generated outputs. As generative AI continues to mature, its integration with other AI techniques, coupled with the development of explainable models, promises to unlock new frontiers in personalized and proactive healthcare.

Looking ahead, the future of clinical decision-making will be increasingly shaped by the innovative applications of generative AI across diverse healthcare domains, including mental health and public health. By continuously refining these technologies, upholding ethical standards, and fostering collaboration between AI developers and clinicians, we can harness the full power of generative AI to create a healthcare system that is more efficient, equitable, and ultimately, more human-centered. The journey is ongoing, but the potential to revolutionize patient care through intelligent and generative systems is undeniable, paving the way for a future where clinical decisions are augmented by the power of AI, leading to improved outcomes and a healthier world.

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