Medical Large Language Models and Generative AI in Healthcare: A Survey

Abstract

Medical Large Language Models (MLLMs) and Generative AI are at the forefront of healthcare innovation, offering transformative potential in clinical decision-making, patient care, and medical processes. This survey paper explores the integration of these advanced AI technologies within the healthcare sector, emphasizing their role in enhancing diagnostic precision, streamlining workflows, and improving patient outcomes. MLLMs, despite challenges with data quality and interpretability, provide sophisticated solutions for processing medical data, while Generative AI facilitates the creation of synthetic data, essential for training AI models and preserving patient privacy. The application of AI in Clinical Decision Support Systems (CDSS) has significantly improved diagnostic accuracy and treatment efficacy. However, the deployment of AI technologies raises ethical concerns, including data privacy, algorithmic bias, and transparency. Addressing these challenges requires robust privacy-preserving techniques, interdisciplinary collaboration, and strategic planning. The survey highlights the need for continuous research to refine AI models, develop ethical guidelines, and ensure equitable healthcare delivery. As AI technologies evolve, they promise to revolutionize healthcare by enabling more precise, personalized, and efficient patient care, underscoring the importance of strategic implementation and ethical governance in AI deployment. Future research should focus on enhancing AI model interpretability, integrating domain knowledge, and exploring innovative applications to fully realize the potential of AI in transforming healthcare.

1 Introduction

1.1 Overview of MLLMs and Generative AI in Healthcare

Medical Large Language Models (MLLMs) and Generative AI technologies are transforming the healthcare sector by effectively managing the complexity and volume of medical data, thereby enhancing clinical decision-making and patient care. MLLMs, despite challenges related to the quality and quantity of medical vision-text data [1], are essential for advancing AI integration in medicine, offering solutions for processing extensive datasets that support informed decision-making by healthcare professionals.

Generative AI, exemplified by models like GPT-3, holds transformative potential in healthcare through the generation of synthetic data for training AI models, which aids in preserving patient privacy [2]. This capability is crucial for developing personalized healthcare solutions and complying with regulatory standards [3]. Furthermore, the integration of Generative AI in medical imaging and electronic medical records (EMRs) enhances healthcare delivery's efficiency and accuracy [4].

The role of MLLMs and Generative AI also encompasses addressing algorithmic fairness, vital for automated medical image analysis [5]. These technologies contribute to AI interpretability, a significant concern in clinical settings where transparency fosters trust and credibility [6]. Moreover,

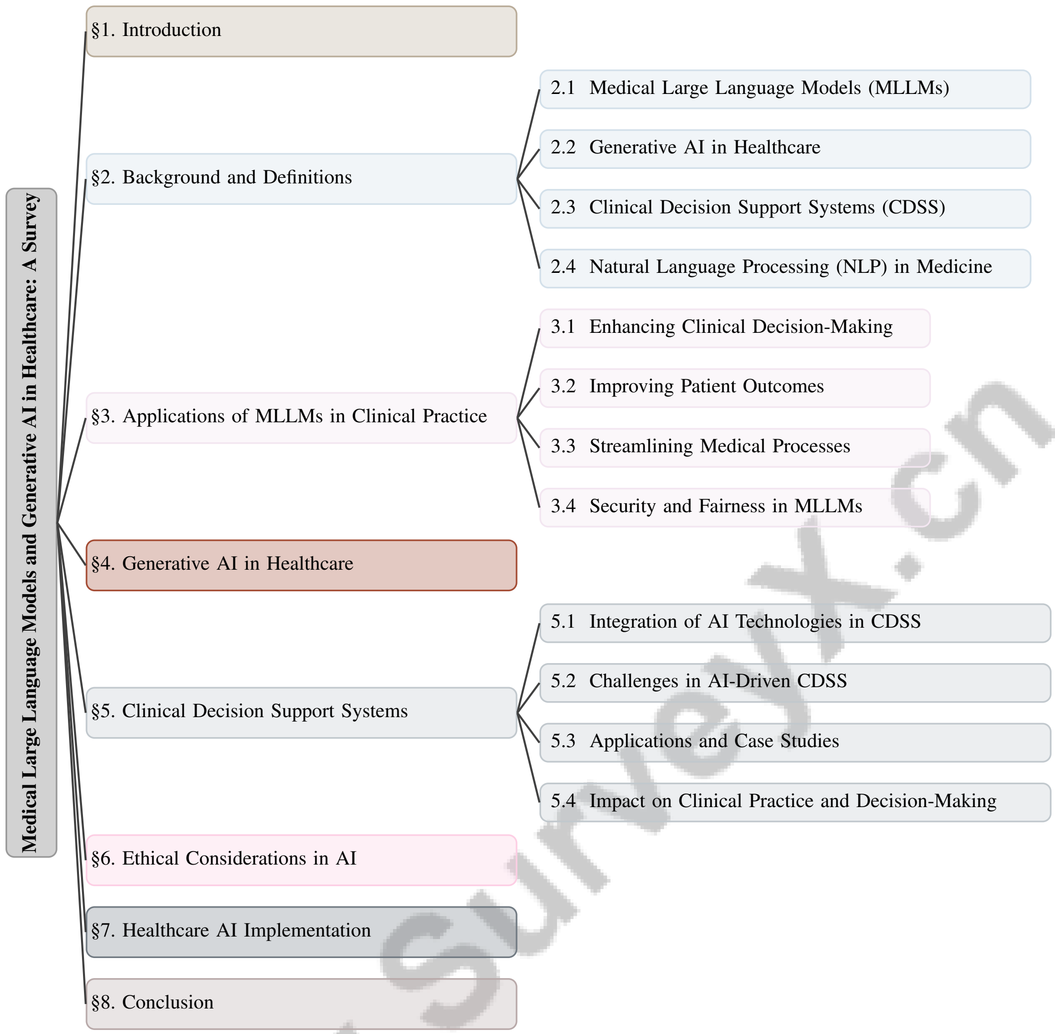

Figure 1: chapter structure

the deployment of multilingual and multimodal MLLMs is crucial for managing linguistic diversity and integrating various data types, essential for global healthcare applications.

Despite their promising applications, ethical challenges persist, including data privacy, algorithmic bias, and the authenticity of AI-generated content, necessitating responsible implementation of these technologies [7]. Continuous evaluation and refinement of AI systems are essential to overcome these challenges and fully harness AI's potential in transforming healthcare [8]. As these technologies evolve, they promise to revolutionize medical science and practice, enabling more precise, personalized, and efficient patient care.

1.2 Significance of AI Integration in Healthcare

Integrating artificial intelligence (AI) technologies into healthcare systems is pivotal for transforming medical diagnostics, patient care, and clinical workflows. AI platforms, such as MLLMs and Generative AI, are increasingly developed for applications including medical diagnostics and patient monitoring, enhancing healthcare delivery's precision and efficiency [9]. The potential of these technologies to improve diagnostic accuracy and treatment effectiveness underscores their significance in modern healthcare [10]. Generative AI, in particular, promises to enhance diagnostic accuracy, clinical workflows, and decision-making processes [11]. The integration of diverse data types, including text, images, and audio, through MLLMs aims to provide a comprehensive understanding of patient data, thus improving clinical decision-making and patient care [12]. However, the use of

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AI in medical imaging and text analysis also raises ethical implications, legal accountability, and data privacy concerns [13].

Challenges such as the rapid evolution of AI terminology and methodologies complicate the standardization process and integration of new concepts into existing frameworks [14]. Additionally, patient apprehension regarding AI technologies may hinder acceptance and effective implementation [15]. Addressing these challenges requires robust privacy-preserving techniques and concerted efforts to bridge gaps in data, technology, and human factors [16]. AI technologies are also crucial for managing the rising prevalence of chronic diseases, where timely detection and intervention are essential [17]. Moreover, the democratization of access to medical diagnostics through advanced MLLMs offers scalable solutions that alleviate the burden on healthcare providers, especially in resource-constrained environments [18]. Collaboration between AI and natural language processing (NLP) enhances healthcare documentation efficiency by reducing burdens associated with electronic health records (EHRs) [19]. As AI continues to evolve, its integration into healthcare systems promises to revolutionize medical practice by enabling more precise, personalized, and efficient patient care. Effective evaluation methods are crucial for assessing AI technologies' performance across diverse medical tasks, ensuring these advancements positively impact healthcare delivery [20].

The core issue explored by [21] is the difficulty in translating AI research into effective clinical applications, where potential benefits remain unrealized. Additionally, AI integration in mental health practices can enhance the diagnosis and treatment of mental illnesses [22]. The survey conducted by [23] highlights LLMs' effectiveness in clinical decision-making and patient care, underscoring their transformative potential. The capabilities of GPT-3 in healthcare delivery, along with its limitations and ethical considerations, are discussed by [4], emphasizing the need for careful deployment. Furthermore, the potential liability of physicians when using AI in medical practice, as explored by [24], addresses legal implications and challenges posed by AI recommendations in clinical decision-making. Lastly, [25] summarizes major AI topics, including applications and limitations in surgery, aiding surgeons in understanding and critically evaluating new AI applications.

1.3 Structure of the Survey

The survey is organized into eight comprehensive sections, each addressing crucial aspects of MLLMs and Generative AI in healthcare. The introductory section provides an overview of MLLMs and Generative AI, establishing their significance by synthesizing insights from various studies. The second section delves into the background and definitions, elucidating key concepts such as MLLMs, Generative AI, Clinical Decision Support Systems (CDSS), and Natural Language Processing (NLP) in medicine, setting the foundation for understanding their applications.

Following this, the survey explores MLLMs' applications in clinical practice, analyzing their impact on clinical decision-making, patient outcomes, and medical processes. This section also addresses security and fairness in MLLM deployment, a critical concern highlighted by [5]. The fourth section focuses on Generative AI, examining its role in medical imaging, clinical documentation, personalized medicine, and drug design.

The fifth section discusses AI integration into CDSS, providing examples and case studies of successful implementations while analyzing their impact on clinical practice. Ethical considerations in AI are addressed in the sixth section, focusing on data privacy, algorithmic bias, transparency, and accountability. The seventh section explores strategies and challenges in implementing AI technologies in healthcare settings, emphasizing strategic planning, stakeholder engagement, and overcoming technical barriers.

Finally, the conclusion summarizes key findings and reflects on future research directions, emphasizing the importance of addressing ethical and implementation challenges to fully realize AI's potential in transforming healthcare. This structured approach guarantees a thorough examination of AI technologies' integration in healthcare, addressing critical aspects such as interpretability, ethical considerations, and practical applications. By analyzing AI's impact on clinical decision support systems, disease diagnosis, and personalized care, the study provides essential insights into the challenges and opportunities faced by researchers and practitioners. This comprehensive analysis enhances understanding of AI's role in improving patient outcomes and offers a roadmap for the responsible implementation of these technologies in healthcare settings [26, 10, 13].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Medical Large Language Models (MLLMs)

Medical Large Language Models (MLLMs) represent a significant leap in AI applications within healthcare, leveraging deep learning and NLP to analyze complex medical data. These models extend traditional language models by addressing multimodal tasks like medical visual question answering (Med-VQA) and medical report generation (MRG), thereby enhancing data analysis capabilities [27]. By integrating visual and textual data, MLLMs effectively manage the heterogeneity of multimodal EHRs, crucial for accurate predictions and improved medical condition management [1]. This integration is essential for identifying regions of interest in medical imaging and processing diverse data types.

Frameworks like Med-2E3 illustrate MLLMs' ability to generate responses based on pixel-level inputs, showcasing their versatility across clinical tasks from diagnosis to predictive modeling. These models significantly enhance clinical prediction accuracy and generalizability, improving patient care quality. However, challenges like the tendency of MLLMs to hallucinate—producing inaccurate or implausible medical information—pose risks to patient safety [6]. Continuous evaluation and refinement are necessary to ensure their reliability and safety in clinical contexts [8].

MLLMs are integral to Clinical Decision Support Systems (CDSS), enabling reliable decision set generation with global and local interpretability through machine learning-enhanced rule sets [26]. Addressing the complexities of relational medical data remains challenging, particularly for critically ill patients. The emergence of Medical Large Vision Language Models (Med-LVLMs) has further advanced medical applications, improving diagnostic accuracy.

Despite advancements, the fairness of MLLMs across diverse demographic groups remains underexplored. The increasing reliance on predictive models in healthcare underscores the need for explainable insights; clinicians require models that provide accurate predictions and clinically relevant information. Recent developments, such as integrating attention mechanisms into convolutional models and using plain-text explanations from large language models, enhance interpretability, empowering clinicians to make informed decisions based on complex clinical data [26, 28, 29, 30, 31]. The demand for interpretable deep learning models in healthcare is accentuated by the need for a deeper understanding of model decision-making processes.

The evaluation of generative clinical LLMs for biomedical NLP and healthcare text generation has showcased their potential to enhance clinical documentation and decision-making. These models, particularly MLLMs, integrate diverse data types—including text, images, and audio—to provide comprehensive insights that improve clinical decision support and patient engagement. Innovations like the PubMedVision dataset demonstrate MLLMs' capacity to address challenges in medical multimodal capabilities, enhancing clinical notes quality and reducing administrative burdens on healthcare professionals. This integration boosts documentation efficiency and fosters a patient-centered care approach, highlighting generative AI's transformative potential in contemporary healthcare practices [1, 32, 12]. The complexity of biomedical texts, characterized by specialized terminology and intricate structures, underscores MLLMs' importance in simplifying and clarifying medical information.

2.2 Generative AI in Healthcare

Generative AI represents a significant advancement in healthcare, utilizing machine learning to generate synthetic data resembling real-world medical datasets. This technology is particularly beneficial in medical imaging, enhancing complex image interpretation through 3D image encoders integration with 2D MLLMs [33]. Employing models like GANs and VAEs, Generative AI facilitates automated medical report generation and streamlines diagnostic processes, improving accuracy and efficiency [11].

Applications of Generative AI in healthcare include clinical documentation, medical imaging, and personalized medicine. Generative models trained on EMR data are pivotal for creating clinical language and EMR representation models, enhancing clinical workflows and patient monitoring precision [2]. Moreover, integrating Generative AI into medical education, scientific publishing, and administrative tasks highlights its potential to revolutionize medical practices by reducing administrative burdens and improving healthcare delivery efficiency [34].

Despite promising applications, Generative AI deployment in healthcare faces challenges, including suboptimal performance in non-question-answering tasks, the absence of large-scale clinical trials, and concerns regarding hallucinations and ethical implications [23]. Additionally, the need for novel evaluation metrics tailored to medical applications underscores the complexity of medical language and reasoning, which existing benchmarks often inadequately address [35].

A comprehensive framework categorizing existing research into realistic, unrealistic, and challenging Generative AI applications is essential to address these challenges. This framework aids in assessing feasibility and risks associated with each application type, ensuring responsible deployment and governance [4]. As Generative AI evolves, its potential healthcare applications are expected to expand, offering innovative solutions for predictive modeling, drug design, and clinical workflow enhancement [11]. These advancements promise to revolutionize healthcare by improving diagnostic accuracy, enabling personalized treatment plans, and enhancing data management efficiency.

2.3 Clinical Decision Support Systems (CDSS)

Clinical Decision Support Systems (CDSS) are essential in modern healthcare, enhancing decision-making by providing evidence-based insights and recommendations. These systems integrate patient-specific data, often from EHRs, with clinical knowledge bases to generate personalized guidance tailored to individual patient needs. CDSS primarily analyze complex medical data from various sources, including EHRs and clinical trials, providing timely, context-sensitive insights essential for navigating intricate clinical scenarios and promoting standardized care. Recent advancements in deep learning have further enhanced these systems' precision and interpretability, enabling predictions of upcoming medical events while addressing privacy concerns through innovative methods like secure multiparty computation [36, 37, 38, 39].

AI integration into CDSS has significantly augmented their capabilities, particularly in improving diagnostic accuracy and treatment effectiveness. AI-driven CDSS have shown potential in areas like breast cancer diagnosis, where understanding factors influencing clinician interactions, such as trust and explainability, is crucial for effective implementation [40]. However, the lack of interpretability in AI-driven CDSS remains a significant barrier to adoption, as clinicians may hesitate to rely on systems with opaque decision-making processes [26].

Biases in machine learning-based CDSS, particularly those using EHR data, pose challenges to their effectiveness. These biases can stem from spurious correlations in patients' clinical histories, leading to misrepresentations of patient health status and hindering CDSS efficacy. To mitigate these challenges, advancements in machine learning-based CDSS have focused on improving data quality and AI model interpretability. For instance, developing large language model-based systems aims to enhance medical decision-making efficiency and accuracy, especially in high-pressure environments like emergency departments [41].

CDSS integration in rural healthcare settings presents unique challenges, as barriers like limited resources and clinician apprehension can impede effective adoption and utilization. Additionally, training and validating CDSS using observational data from the clinic where the DSS is applied, rather than relying solely on randomized clinical trial data, is crucial for ensuring relevance and effectiveness in real-world settings. Privacy concerns are paramount, necessitating privacy-preserving methods in CDSS that utilize patient data [42].

CDSS have demonstrated improvements in adherence to clinical guidelines and enhanced antibiotic stewardship by integrating with EHRs, supporting clinicians in informed decision-making. However, the complexity of existing CDSS recommendations can lead to preventable errors, underscoring the need for systems that are both comprehensive and user-friendly. The cumbersome process of entering extensive patient data into CDSS can contribute to clinician burnout and data entry errors, complicating their use [43].

2.4 Natural Language Processing (NLP) in Medicine

Natural Language Processing (NLP) plays a transformative role in medicine, enabling the analysis and interpretation of vast amounts of unstructured clinical data, such as EMRs. NLP facilitates machines in comprehending and processing human language, allowing for meaningful insights extraction from clinical notes and enhancing predictive models [25]. The application of NLP in

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healthcare extends to the automatic processing and analysis of clinical notes, a challenge that remains underexplored despite the potential of AutoML techniques to address it [44]. This capability is essential for improving healthcare outcomes by ensuring accurate identification and interpretation of critical medical information.

The development of large pre-trained language models, such as GatorTronGPT, has significantly advanced NLP technologies, enhancing medical data interpretation accuracy and efficiency by generating synthetic clinical text and leveraging large-scale clinical data [45]. These models have streamlined clinical documentation processes, allowing healthcare professionals to focus more on patient care by alleviating documentation burdens [19]. Furthermore, transforming EHR data into serialized textual representations, known as pseudo-notes, has improved clinical data interpretability and integration, enhancing medical information accessibility [46].

Despite these advancements, NLP systems in clinical settings encounter challenges such as potential biases in AI algorithms and the necessity for human oversight to accurately interpret AI findings [10]. The black-box nature of deep learning models, which underpin many NLP systems, complicates their transparency and explainability, making it challenging for end users to trust the model's predictions in critical healthcare applications [47]. Addressing these issues is vital for building trust and reliability among healthcare providers.

Moreover, NLP is crucial for understanding biases related to sex and gender differences in health data, ensuring equitable healthcare outcomes [48]. The challenges MLLMs face, such as data quality and diversity, linguistic bias, and ensuring fairness and interpretability in multilingual contexts, further highlight the complexity of deploying NLP in medicine [49]. Existing research has made notable progress in lexical and syntactic simplification, improving the accessibility of medical information for consumers [50].

3 Applications of MLLMs in Clinical Practice

The integration of Medical Large Language Models (MLLMs) is revolutionizing clinical practice by enhancing efficiency, decision-making, and patient outcomes. This section examines MLLMs' impact on clinical decision-making, a cornerstone of effective patient care. As illustrated in Figure 2, the applications of MLLMs in clinical practice are multifaceted, highlighting their roles in enhancing clinical decision-making, improving patient outcomes, streamlining medical processes, and addressing security and fairness. Key areas of focus include the integration of advanced techniques and generative AI models, adherence to clinical guidelines, workflow efficiency, and the mitigation of security and fairness challenges. Leveraging advanced NLP and machine learning, MLLMs assist clinicians in navigating complex medical data, thereby influencing decision quality.

3.1 Enhancing Clinical Decision-Making

MLLMs advance clinical decision-making by employing cutting-edge NLP and deep learning techniques, enabling clinicians to interpret complex datasets with greater precision. Their integration into Clinical Decision Support Systems (CDSS) improves decision efficiency and personalizes predictions, fostering trust among clinicians [41]. Multi-agent CDSS utilizing advanced LLMs assist emergency department staff in triage and treatment planning, enhancing outcomes and operational efficiency [51]. Frameworks like Med-2E3, which merge 3D and 2D feature extraction, exemplify MLLMs' transformative impact on clinical decision-making [27].

Figure 3 illustrates the role of Multimodal Large Language Models (MLLMs) in enhancing clinical decision-making. Key areas highlighted in the figure include their integration into CDSS for precision improvement and multi-agent support, the application of medical visual question answering using PubMedVision, and the contribution of generative AI models like GatorTronGPT and ChatGPT in medical documentation and decision-making. MLLMs trained with PubMedVision excel in medical visual question answering, improving decision-making through precise information retrieval [1]. Adaptive questionnaires reduce clinician data entry workload, enhancing CDSS usability [43]. Interpretability in deep learning models is essential, as demonstrated by SHAMSUL's use of local interpretability methods to assess prediction significance [6]. CABIA improves biomedical image analysis accuracy, supporting informed clinical judgments [52].

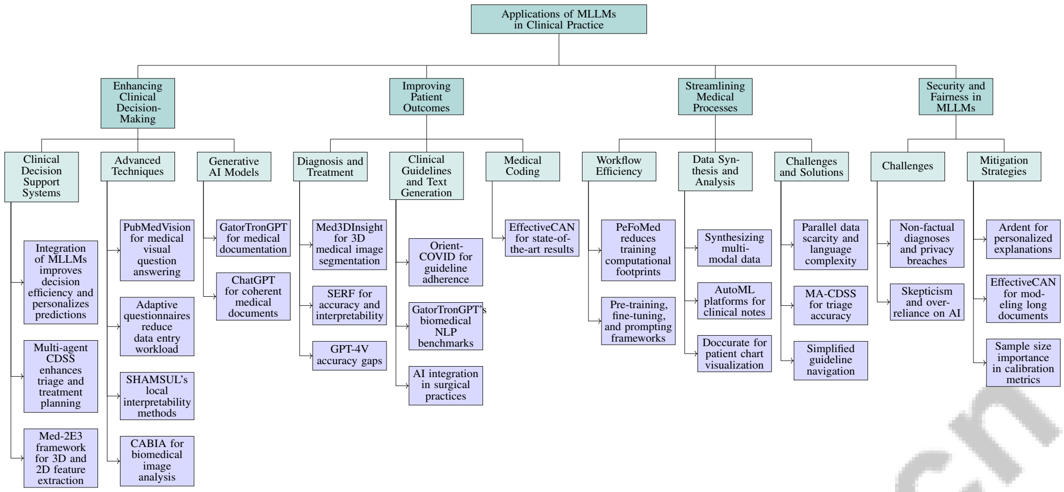
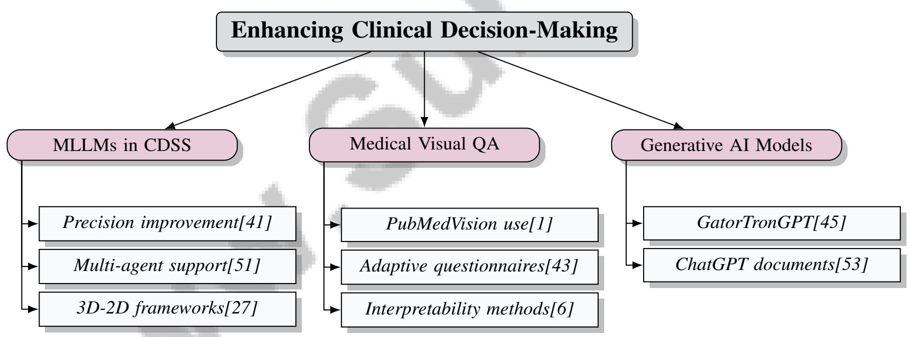


Figure 2: This figure illustrates the applications of Medical Large Language Models (MLLMs) in clinical practice, highlighting their roles in enhancing clinical decision-making, improving patient outcomes, streamlining medical processes, and addressing security and fairness. Key areas include the integration of advanced techniques and generative AI models, adherence to clinical guidelines, workflow efficiency, and mitigation of security and fairness challenges.

Generative AI models like GatorTronGPT enhance medical documentation and generate human-like clinical text, improving communication among healthcare professionals [45]. ChatGPT's ability to produce coherent medical documents and summarize research findings further enriches clinical decision-making [53].



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3.2 Improving Patient Outcomes

MLLMs enhance patient outcomes by integrating advanced NLP and machine learning techniques. They enable accurate diagnoses and personalized treatment plans through effective data interpretation. Frameworks like Med3DInsight have achieved notable improvements in patient outcomes, particularly in 3D medical image segmentation and classification [33]. Models like SERF enhance accuracy and interpretability, fostering clinician trust in AI-generated insights [54]. Despite advancements, models such as GPT-4V still exhibit accuracy gaps across specialties, necessitating ongoing improvements [55].

MLLMs also improve adherence to clinical guidelines, as demonstrated by Orient-COVID's impact on clinician compliance [56]. Their ability to capture clinical decision interdependencies enhances predictive performance, underscoring their potential in CDSS [57]. Additionally, MLLMs facilitate the generation of clinically relevant text, as evidenced by GatorTronGPT's performance on biomedical NLP benchmarks [45]. This capability is critical for ensuring healthcare providers access accurate information.

AI integration into surgical practices promises to revolutionize training and patient care, enabling surgeons to incorporate AI-driven insights effectively [25]. Models like EffectiveCAN achieve state-of-the-art results in medical coding tasks, enhancing prediction accuracy and improving patient outcomes [51].

3.3 Streamlining Medical Processes

MLLMs streamline medical processes, enhancing healthcare delivery efficiency and effectiveness. By employing advanced machine learning and NLP, MLLMs facilitate medical workflows from diagnosis to patient management and predictive analytics. Models like PeFoMed reduce training computational footprints, increasing accessibility for medical applications [58]. This accessibility is crucial for deploying MLLMs across diverse settings, enhancing AI-driven solution scalability.

A structured overview categorizes research into pre-training, fine-tuning, and prompting frameworks, contributing to efficient medical processes [23]. MLLMs' ability to synthesize multimodal data streamlines clinical workflows [59]. AutoML platforms for clinical notes enhance patient outcomes by improving analysis and diagnostic accuracy [44]. This approach alleviates cognitive load, allowing healthcare professionals to focus on patient care while ensuring critical insights are not overlooked. Tools like Doccurate enable efficient curation and visualization of large patient charts, enhancing data usability [60].

Challenges such as parallel data scarcity and biomedical language complexity necessitate innovative approaches to streamline processes [50]. Intelligent decision support systems like MA-CDSS improve triage accuracy and decision-making in emergency care, highlighting MLLMs' potential to enhance outcomes and alleviate overcrowding [41]. Simplified guideline navigation reduces cognitive load and improves decision accuracy, optimizing clinical decision support and guideline adherence [56].

3.4 Security and Fairness in MLLMs

Deploying MLLMs in clinical settings requires thorough security and fairness assessments to ensure safe and equitable healthcare. A primary challenge is the potential for non-factual medical diagnoses and privacy breaches, which can have severe consequences [61]. Skepticism or over-reliance on AI-generated advice poses risks, particularly when inaccurate, leading to misdiagnoses [40].

To mitigate these risks, models like Ardent emphasize personalized explanations to enhance user engagement and decision-making [62]. EffectiveCAN addresses security and fairness by efficiently modeling long documents with attention mechanisms, improving performance on rare labels and contributing to equitable healthcare [51]. Research on sample size's importance in evaluating calibration metrics underscores its role in addressing security and fairness issues in MLLMs [5]. This consideration is vital for ensuring MLLMs provide reliable and unbiased outputs across diverse populations.

4 Generative AI in Healthcare

Generative AI is transforming healthcare by enhancing clinical practices and patient outcomes, particularly through advancements in medical imaging that improve diagnostic accuracy and efficiency.

4.1 Generative AI in Medical Imaging

Generative AI significantly enhances medical imaging, utilizing advanced machine learning techniques to improve diagnostic precision. The Plane-Slice-Aware Transformer (PSAT) in Med3DInsight exemplifies this by integrating Generative AI into three-dimensional imaging, thereby enhancing analysis accuracy [33]. Models such as Gemini surpass traditional frameworks like GPT-4V in medical image classification, highlighting the necessity of accurate interpretation for patient outcomes [63]. MedXChat further illustrates versatility by supporting text report generation and visual question-answering (VQA) tasks [64].

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As shown in Figure 4, this figure illustrates the hierarchical structure of key advancements in Generative AI within the medical imaging domain, emphasizing model enhancements, the role of vision-language models, and the transformative potential of AI technologies. Vision-Language Models (VLMs) enhance medical report generation and VQA, leading to improved healthcare outcomes [65]. Their ability to process multimodal datasets is crucial for comprehensive medical analysis [20]. MLeVLM outperforms existing models in recognition, detail extraction, diagnosis, and knowledge application [66]. Generative AI's transformative role in medical imaging is underscored by its potential to revolutionize imaging techniques [13]. MedPLIB achieves state-of-the-art performance in medical visual language tasks, particularly in pixel grounding evaluations, which are vital for accurately identifying regions of interest in medical images [67].

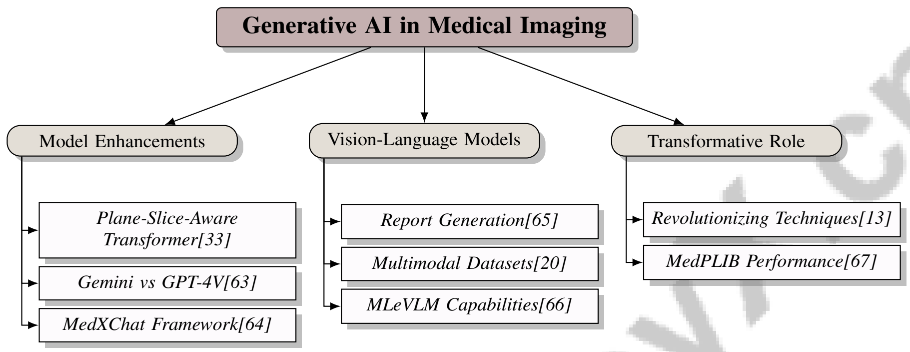


Figure 4: This figure illustrates the hierarchical structure of key advancements in Generative AI within the medical imaging domain, emphasizing model enhancements, the role of vision-language models, and the transformative potential of AI technologies.

4.2 Text Generation and Clinical Documentation

Generative AI revolutionizes clinical documentation by enhancing text generation efficiency and accuracy. Advanced architectures, including Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Generative Adversarial Networks (GANs), enable automatic generation of structured clinical notes from patient-clinician interactions, supporting standardized documentation formats like SOAP and BIRP [50, 60, 32, 68, 69].

Generative AI's application in text analysis improves clinical report accuracy [13], streamlining documentation and allowing healthcare professionals to focus on patient care. Language Model Augmented Retrieval (LMAR) systems, such as Ask Avo, enhance clinical documentation by incorporating visual citation cues and improving information retrieval [69]. AutoML tools automate clinical notes analysis, enhancing accuracy and capturing critical insights [44].

4.3 Personalized Medicine and Synthetic Data

Generative AI revolutionizes personalized medicine by generating synthetic data that enhances treatment precision and customization. Adaptive attention models, combined with domain knowledge, improve the understanding of medical terms, advancing personalized healthcare solutions [70]. The HAIM-MIMIC-MM dataset, integrating MIMIC-IV and MIMIC Chest X-ray databases, supports AI model training and evaluation essential for personalized medicine applications [71].

Generative AI's ability to produce realistic synthetic data is crucial for developing personalized treatment plans and improving patient outcomes [3]. The PeFoMed framework utilizes Generative AI for enhanced medical report generation, leveraging large language models (LLMs) as versatile decoders for multimodal applications [58]. The MedTrinity dataset facilitates large-scale pre-training of multimodal medical AI models, supporting sophisticated integration of diverse data types for personalized medicine [72]. Future research should prioritize unsupervised methods and ethical concerns related to automated systems, along with exploring interpretability methods to ensure AI-driven insights are comprehensible for healthcare providers [50, 28].

4.4 Advancements in Predictive Performance and Drug Design

Generative AI significantly enhances predictive performance and drug design, streamlining drug discovery and improving clinical outcomes. Advanced techniques, such as deep generative models and automated machine learning, facilitate the creation of novel compounds and predictive models essential for identifying drug candidates and predicting their efficacy and safety [44, 70, 3]. The processing of vast biomedical data and generation of synthetic datasets allows comprehensive exploration of chemical spaces, aiding in discovering new therapeutic agents.

Frameworks like Asclepius, covering diverse medical specialties, demonstrate Generative AI's potential to improve predictive performance across various contexts [55]. Incorporating interpretability methods, as shown by the SHAMSUL approach, enhances transparency and trustworthiness of AI-assisted diagnoses [6]. Future research should aim to improve LLM accuracy in generating search strategies and summarizing information, and explore new applications for LLMs in evidence synthesis [73]. Advancing Generative AI capabilities promises to revolutionize healthcare delivery and patient outcomes.

5 Clinical Decision Support Systems

The integration of artificial intelligence (AI) technologies has significantly enhanced Clinical Decision Support Systems (CDSS), improving clinical decision-making processes. This section delves into the transformative impact of AI on CDSS, focusing on its role in diagnostics and treatment strategies. The following subsections will explore specific AI technologies within CDSS and their contributions to clinical outcomes.

5.1 Integration of AI Technologies in CDSS

AI technologies have greatly advanced CDSS functionality, offering clinicians sophisticated tools to enhance diagnostic accuracy and treatment efficacy. Key innovations include large language models (LLMs) and explainable AI, which improve complex medical data interpretation and feature selection, thereby optimizing decision-making in healthcare datasets [74]. These developments highlight AI's potential to transform CDSS through advanced data processing.

Frameworks evaluating the impact of AI-generated explanations on clinician trust and diagnostic agreement have emerged, providing structured assessments of AI explainability's influence on decision-making. Specialized LLMs like Ask Avo exemplify AI's ability to deliver reliable clinical information, enhancing CDSS recommendation precision [69].

Despite the promise of multimodal data integration, challenges persist due to the lack of standardized methodologies for diverse data processing, limiting AI systems' performance in healthcare [71]. Frameworks like PeFoMed showcase effective AI integration by enabling multimodal data processing, thereby improving medical large language models' (MLLMs) accuracy and applicability in clinical contexts [58].

AI technologies also facilitate real-time recommendations based on dynamic clinical inputs. For instance, machine learning classifiers analyzing ventilator waveform data demonstrate AI's capacity to provide accurate, contextually relevant recommendations [75]. Privacy-preserving methods, such as DP-RuL, integrate Monte-Carlo Tree Search (MCTS) with local differential privacy to balance utility and privacy, ensuring patient data security [42].

The effectiveness of Med-2E3 in modeling inter-slice relationships and intra-slice details mimics radiologists' attention during image analysis, showcasing AI's advanced capabilities in CDSS [27]. Additionally, the Ardent meta-system dynamically learns to provide tailored explanations, optimizing human-AI collaboration [62].

Moreover, integrating machine learning and computational intelligence with traditional image processing techniques enhances CDSS functionality by improving biomedical image analysis accuracy and efficiency [52]. Frameworks emphasizing transparency, data standardization, and regulatory compliance are crucial for aligning AI-driven CDSS with clinical needs and ethical standards [8].

5.2 Challenges in AI-Driven CDSS

AI-driven CDSS face several challenges, primarily due to healthcare complexities and current AI model limitations. The opacity of AI models can lead to transparency deficits among clinicians, compounded by insufficient user studies that fail to address clinician needs and limited implementation of explainable AI (XAI) [76].

The reliance on biomedical literature quality poses another challenge, as demonstrated by the Clinical Evidence Engine, which may not cover all clinical scenarios [77]. This limitation underscores the need for diverse and representative data to train AI algorithms effectively, a gap exacerbated by the historical underrepresentation of certain demographics, such as women, in clinical trials [48]. Insufficient diverse data perpetuates biases in AI algorithms, restricting their applicability across varied patient populations.

Practical challenges, including alert fatigue and variability in system integration, hinder AI solutions' incorporation into clinical workflows. These factors contribute to resistance from healthcare professionals, who may struggle with data biases and model transparency issues [78]. Additionally, monocentric study designs and reliance on medical students may not accurately reflect real-world clinical decision-making, limiting findings' generalizability [56].

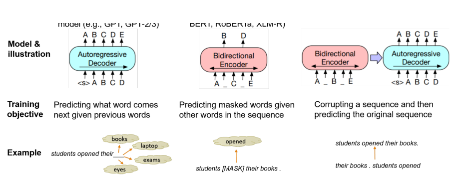
Furthermore, implementing adaptive questionnaires to facilitate patient data collection may lack universal applicability, especially where clinicians have direct access to electronic health records [43]. This limitation highlights the need for flexible, context-specific solutions in AI-driven CDSS.

5.3 Applications and Case Studies

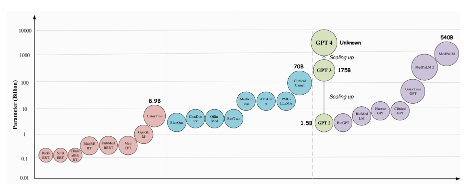
Successful AI-driven CDSS implementations demonstrate their potential to enhance clinical decision-making and patient care. One notable example is the use of a provenance template service with a non-repudiation framework, ensuring secure and verifiable decision-making evidence, thus enhancing CDSS reliability [79].

Implementing adaptive questionnaires within CDSS has improved patient data collection efficiency, with positive clinician feedback on usability and impact on clinical workflows [43]. This approach streamlines data entry and reduces cognitive load, allowing healthcare providers to focus more on patient care.

These case studies illustrate AI-driven CDSS's transformative potential in modern healthcare, emphasizing their capacity to improve diagnostic accuracy, enhance clinical workflows, and ensure accountability in clinical decisions. As AI systems advance, they are expected to play an increasingly essential role in healthcare delivery, providing innovative solutions that enhance disease diagnosis, treatment recommendations, and patient engagement. These systems leverage large datasets to improve clinical efficiency, increase diagnostic accuracy, reduce costs, and minimize human errors. The integration of interpretable AI technologies, such as wearables and telemedicine, is crucial for fostering provider trust, ensuring AI-generated outcomes are both accurate and comprehensible. This evolution in AI capabilities is anticipated to revolutionize personalized medicine and optimize population health management, ultimately leading to improved patient outcomes and a more efficient healthcare system [26, 10].



(a) Model illustration of training objective and example for different types of sequence modeling tasks[80]



(b) Comparison of Parameter Sizes Across Different Language Models[23]

Figure 5: Examples of Applications and Case Studies

As illustrated in Figure 5, Clinical Decision Support Systems (CDSS) are pivotal in healthcare, enhancing decision-making through data-driven insights and advanced computational models. The figure highlights intricate applications and case studies relevant to these systems, showcasing their adaptability and efficacy in managing complex medical data. The first subfigure explores sequence modeling tasks, highlighting training objectives and examples across three methodologies: autoregressive decoding, bidirectional encoding, and autoregressive decoding with masking. This comparative diagram emphasizes the dynamic information flow within these models, crucial for processing and interpreting sequential medical data. The second subfigure presents a comparative analysis of parameter sizes across various language models, categorized into BERT-like, ChatGLM/LLaMA-like, and GPT/PaLM-like models. By illustrating the scale and complexity of these models, the chart underscores the computational power required to support sophisticated CDSS, ultimately aiding in delivering precise and personalized healthcare solutions [80, 23].

5.4 Impact on Clinical Practice and Decision-Making

AI-driven Clinical Decision Support Systems (CDSS) have significantly transformed clinical practice and decision-making, enhancing healthcare delivery's accuracy, efficiency, and reliability. These systems improve patient safety and streamline workflows, ensuring adherence to clinical guidelines, with studies indicating an average improvement of 5.8% in patients receiving desired care [81]. The integration of AI technologies into CDSS has enhanced predictive performance and interpretability, improving their utility in clinical environments [82].

The effectiveness of AI-driven CDSS is highlighted by their ability to predict treatment outcomes and suggest improvements, providing viable decision support where new treatments are not yet deployed [83]. For example, the pseudo-notes method has shown superior performance in predicting antibiotic susceptibility, emphasizing AI's potential to enhance clinical practice [46].

As illustrated in Figure 6, the impact of AI-driven CDSS on clinical practice encompasses enhancements in practice, integration challenges, and future directions for development. This visual representation underscores the multifaceted role of CDSS in improving clinical workflows while also highlighting the challenges that must be addressed for optimal implementation.

Furthermore, integrating synthetic data generators with frameworks like FHIR facilitates effective validation and deployment of machine learning-driven CDSS tools, improving clinical decision-making [84]. The necessity for context-sensitive, user-friendly, and seamlessly integrated CDS systems is crucial for enhancing decision-making and improving patient outcomes [85].

However, challenges persist in designing and integrating AI-CDSS, necessitating significant improvements to enhance clinician trust and usability [86]. The potential for logical fallacies in knowledge artifacts (KAs) requires semantic verification during the authoring phase, with SMT model checking serving as a means to enhance KA reliability [87].

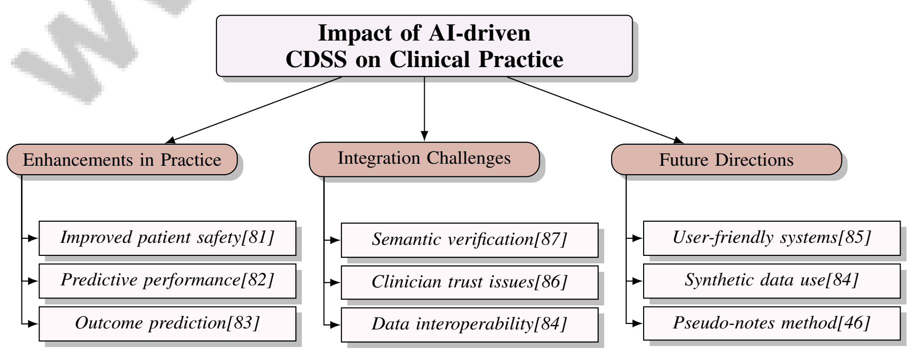


Figure 6: This figure illustrates the impact of AI-driven Clinical Decision Support Systems (CDSS) on clinical practice, highlighting enhancements in practice, integration challenges, and future directions for development.

6 Ethical Considerations in AI

6.1 Data Privacy and Security

AI's integration into healthcare demands rigorous data privacy and security protocols to ensure ethical use. The necessity for vast datasets in AI training and the complexity of embedding AI in medical workflows highlight the need for robust privacy-preserving strategies. The opaque nature of AI and risks of re-identifying anonymized data necessitate strong privacy measures to maintain trust in clinical environments [52]. Balancing patient data privacy with data sharing for AI training is a critical challenge [8]. Systems like MA-CDSS emphasize patient privacy by incorporating a 'human-in-the-loop' approach, which enhances accountability [41]. This is crucial given the potential for personal biases and misunderstanding patient preferences to impact care [88].

Data privacy is further complicated by EHR data synthesis and utilization, requiring careful handling to protect sensitive information. Privacy concerns are particularly significant when implementing generative AI models, necessitating robust frameworks to secure patient confidentiality [51]. The reliance on high-quality annotated datasets for AI training underscores the need for effective data management strategies [47].

6.2 Algorithmic Bias and Fairness

AI systems in healthcare face challenges of algorithmic bias and fairness, essential for equitable healthcare delivery. Bias often results from training on non-diverse datasets, leading to unequal outcomes. The literature addresses AI's ethical implications in medicine, focusing on content accuracy and misuse potential, though comprehensive solutions remain scarce [53]. The opacity of AI decisions can lead to over-reliance by clinicians, risking diagnostic errors [76]. The complexity of AI models complicates providing understandable explanations, affecting user trust and feedback [26, 47]. Inconsistent interpretability across pathologies can mislead interpretations [6]. Addressing these issues requires enhancing AI transparency and explainability [28].

Efforts to mitigate bias include frameworks incorporating ethical reasoning in AI systems [88]. However, minority underrepresentation and algorithmic biases from training data remain significant challenges [7]. Calibration metrics are crucial to ensure fair AI performance across diverse populations [5]. AI integration in clinical workflows raises ethical questions and challenges like high patient volumes, interoperability, usability barriers, and AI recommendation reliability [61]. Medical application benchmarks often overlook accuracy, safety, and ethical considerations [34].

6.3 Transparency and Explainability

Transparency and explainability are crucial for deploying AI in healthcare, as they build trust and ensure ethical practices. Large pre-trained language models must provide clear explanations for their decisions to be applicable in real-world settings [80]. This transparency fosters trust among healthcare professionals and allows scrutiny for biases and errors. The ECCOLA Deployment Model promotes ethical communication throughout AI development, enhancing transparency from the outset [89]. The GREAT PLEA ethical principles guide the ethical use of generative AI, emphasizing transparency as essential [90].

Recognizing latent biases in AI algorithms necessitates proactive measures for transparency and fairness [91]. Diverse datasets, transparency, and interdisciplinary collaboration are critical for addressing AI bias and ensuring fairness [92]. Explainability is vital for maintaining trust and ensuring patient-centered care [30]. Robust ethical frameworks, continuous monitoring, and education are essential to address ethical challenges in AI development [93]. Definitions of explainability, standardized evaluation metrics, and fidelity issues recognition are crucial for enhancing AI transparency and reliability [47].

6.4 Accountability and Ethical Governance

Accountability and ethical governance are vital for responsible AI deployment in healthcare. Embedding ethical considerations throughout AI development minimizes harms and maximizes benefits. The ECCOLA Deployment Model exemplifies integrating ethical principles into AI systems, enhancing stakeholder involvement [89]. Emerging trends focus on improving AI accuracy and ethical use, with guidelines for integrating large language models [53]. These are essential for addressing AI deployment ethics, especially in sensitive areas like mental health and surgery.

Robust ethical frameworks for generative AI in healthcare foster trust and accountability [90]. Continuous monitoring and auditing are necessary to maintain AI integrity and trustworthiness. The EbD-AI framework facilitates ethics integration into design methodologies [88]. Researchers are encouraged to document NLP tool usage, enhancing transparency and ethical governance [7].

7 Healthcare AI Implementation

7.1 Strategic Planning and Data Management

Strategic planning and data management are pivotal for embedding AI technologies into healthcare systems, addressing challenges related to external conditions, strategic change management, and transformation of healthcare practices [94]. Effective planning includes optimizing information-preserving relational databases, which enhance AI's ability to manage complex healthcare data through feature ranking and optimization techniques [95]. Data management, crucial for data integrity and accessibility, involves developing specialized AutoML tools for clinical notes to improve AI-driven clinical decision support systems (CDSS) [44].

Integrating AI-assisted CDSS requires comprehensive training for healthcare professionals [9]. Future research should focus on user-centered explainable AI (XAI) solutions, extensive user studies, and interdisciplinary approaches to enhance XAI integration in CDSS [76]. Robust regulatory frameworks, algorithmic transparency, and collaboration between AI developers and healthcare practitioners are essential for successful AI implementation, improving patient outcomes and clinical efficiency [21].

7.2 Stakeholder Engagement and Interdisciplinary Collaboration

Effective stakeholder engagement and interdisciplinary collaboration are critical for optimizing AI applications in healthcare. Addressing AI deployment challenges necessitates strategic implementation strategies and collaboration among stakeholders [94]. Collaboration between AI researchers and healthcare professionals ensures AI technologies align with clinical needs and ethical standards, enhancing AI integration into clinical workflows [11]. Insights from general practitioners (GPs) reveal the importance of understanding their experiences with AI technologies to facilitate effective collaboration and adoption [19].

Ethical AI deployment requires collaboration among healthcare and technology stakeholders to ensure responsible AI use [96]. This fosters a comprehensive understanding of AI's ethical implications and supports the development of guidelines prioritizing patient safety, data privacy, and algorithmic fairness.

7.3 Regulatory Compliance and Ethical Considerations

Implementing AI in healthcare necessitates robust regulatory compliance and ethical considerations to ensure responsible deployment. The lack of comprehensive regulatory frameworks underscores the need for improved guidelines focusing on patient consent and data protection [8]. Future research should develop inclusive AI systems that prioritize patient engagement and transparency in AI decision-making [13]. Establishing robust ethical guidelines and enhancing transparency are critical for equitable AI access in healthcare [9].

Regulatory compliance guidelines must be flexible to address diverse challenges posed by AI in different healthcare settings [97]. Future research should diversify training datasets, develop ethical guidelines, and explore generative AI implications to ensure responsible AI development [92]. Ongoing monitoring and evaluation of AI systems are necessary to ensure adherence to ethical standards and positive contributions to healthcare delivery [93].

7.4 Overcoming Technical and Resource Barriers

Addressing technical and resource barriers is essential for AI deployment in healthcare. Developing interpretable machine learning systems is crucial for building clinician trust and ensuring usability

[98]. High-quality data is pivotal for AI model accuracy and reliability [99]. Addressing biases and establishing ethical guidelines for AI use are critical for overcoming barriers. Future research should enhance model robustness and establish frameworks for continual learning and adaptation in clinical settings [99].

Integrating differential privacy in deep learning models to generate synthetic biomedical data is promising for overcoming data scarcity. Improving communication efficiency in federated learning and developing new aggregation techniques for heterogeneous data are essential strategies for addressing technical challenges [16]. Developing explainable AI and enhancing data governance are critical for fostering public trust and creating robust training programs for healthcare professionals [78].

7.5 Enhancing AI Model Performance and Trust

Enhancing AI model performance and building trust are critical for successful AI deployment in healthcare. Systems like the Clinical Evidence Engine exemplify AI's potential to support clinicians, especially in low-resource settings [77]. Optimizing data quality and ensuring algorithm robustness are essential for improving AI model performance. Developing interpretable machine learning systems is vital for building clinician trust by offering transparent insights into AI decision-making [98].

Addressing biases and establishing ethical guidelines are crucial for responsible AI implementation. This includes ensuring AI systems produce accurate and interpretable outcomes, fostering responsible clinician-AI collaboration, and mitigating risks associated with mistrust [26, 91, 10, 13]. Future research should enhance model robustness and establish frameworks for continual learning. Integrating differential privacy in deep learning models to generate synthetic biomedical data is promising for overcoming data scarcity.

Improving communication efficiency in federated learning and developing new aggregation techniques for heterogeneous data are essential strategies for addressing technical challenges [16]. Developing explainable AI and enhancing data governance are critical for fostering public trust and creating robust training programs for healthcare professionals [78].

8 Conclusion

8.1 Challenges and Future Directions

The integration of artificial intelligence (AI) technologies into healthcare presents substantial challenges that demand dedicated research and development to fully realize their transformative potential. A key challenge lies in enhancing the adaptability and robustness of Medical Large Language Models (MLLMs) to effectively manage diverse clinical scenarios. Future research should focus on refining interpretability methods, exploring multimodal data integration, and actively involving domain experts to improve AI's practical applicability in medical diagnostics. Additionally, advancing Computer-Assisted Biomedical Image Analysis (CABIA) methods to ensure better generalizability across various imaging modalities and enhancing real-time processing capabilities are crucial areas for future exploration.

Ethical considerations are paramount, necessitating the development of practical guidelines for AI deployment in healthcare. This involves addressing AI's impact on patient-provider relationships and ensuring alignment with ethical standards. Future efforts should concentrate on creating standardized protocols for AI implementation, fostering interdisciplinary collaboration, and integrating ethical considerations into AI applications. Establishing frameworks for explainability that comply with legal and ethical standards is vital for promoting collaboration and addressing the challenges posed by AI technologies.

Enhancing AI systems' transparency and trustworthiness requires efficient interpretability methods and the integration of domain knowledge. Future research should explore user-centered designs for interpretability tools to improve understanding and adoption among healthcare professionals. Expanding benchmarks to include diverse datasets will further enhance the applicability and reliability of AI models in healthcare.

Interdisciplinary collaborations are crucial for improving AI model performance in non-question-answering tasks and addressing ethical and safety concerns in clinical applications. Exploring semi-supervised learning techniques can enhance systems' understanding of scenarios where both human and AI policies may falter, thereby refining decision-making processes. Emphasizing privacy-preserving methods, such as optimizing differential privacy techniques for specific clinical contexts, is essential for safeguarding data security and patient confidentiality.

8.2 Research Opportunities

The landscape of AI in healthcare offers numerous research opportunities encompassing both technical and ethical dimensions. A critical area for exploration is developing frameworks to monitor AI biases, which is essential for ensuring equitable healthcare delivery. Engaging healthcare stakeholders and investigating patient perspectives on AI applications will provide valuable insights into the practical challenges and ethical considerations of AI integration in clinical settings.

Addressing the limitations of generative AI technologies is also essential. Future research should investigate new applications of generative AI in healthcare, such as enhancing personalized medicine and improving clinical decision-making processes. Establishing robust regulatory frameworks will facilitate the safe and effective implementation of these technologies, ensuring alignment with ethical standards and patient safety requirements.

Fostering interdisciplinary collaborations among AI researchers, healthcare professionals, and ethicists is vital for developing innovative solutions that address both technical challenges and ethical concerns. By focusing on these research opportunities, the healthcare sector can fully harness AI technologies to enhance patient care and improve clinical outcomes.

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