Integration of AI in Healthcare: A Survey on Generative AI and Large Language Models in Anesthesia and Medical Practices

Abstract

The integration of artificial intelligence (AI) technologies, particularly generative AI and large language models (LLMs), into healthcare marks a transformative era in medical practices, enhancing diagnostic precision, treatment personalization, and operational efficiencies. This survey explores the multifaceted applications of AI in healthcare, with a focus on anesthesia, highlighting its role in monitoring patient vitals, predicting outcomes, and optimizing delivery to improve patient safety and clinical outcomes. Generative AI's capacity to create synthetic data addresses data scarcity, while LLMs enhance medical information processing, supporting comprehensive clinical decision-making. However, challenges such as data privacy, algorithmic bias, and the need for transparency and explainability persist, necessitating robust ethical frameworks and interdisciplinary collaboration to ensure responsible AI deployment. The survey emphasizes the importance of optimizing AI model capabilities and efficiency, integrating AI across diverse medical domains, and fostering collaborative research to advance AI-driven healthcare solutions. By addressing these challenges and leveraging AI's potential, the healthcare sector can achieve significant improvements in patient care and operational efficiencies, paving the way for innovative and accessible medical practices.

1 Introduction

1.1 Contextualizing AI in Healthcare

The integration of artificial intelligence (AI) into healthcare represents a significant advancement, enhancing diagnostic accuracy, personalizing treatment, and optimizing patient monitoring. AI technologies, particularly generative AI and large language models (LLMs), are revolutionizing healthcare by harnessing data analysis and decision support capabilities. In metaverse-enabled digital healthcare systems, AI can utilize extensive personal health data while safeguarding privacy [1]. Moreover, AI enhances communication regarding the biological, psychological, and social dimensions of medical conditions, which are often neglected in traditional healthcare frameworks [2].

Generative models of brain dynamics exemplify the intersection of neuroscience, AI, and system dynamics, providing insights into brain function and potential interventions [3]. In radiology, LLMs improve diagnostic tools, leading to more accurate and efficient practices [4]. AI's role in mental health is highlighted through its application in explainable solutions for diagnosing disorders [5] and its potential in interventions for conditions like schizophrenia [6].

The emergence of multi-modal LLMs, such as ChatGPT, underscores AI's potential across various medical domains [7], though challenges remain in modulating LLM behavior to ensure non-toxicity and resilience against misuse [8]. Integrating physiological data into LLMs aims to enhance empathy, addressing limitations in existing chatbots' emotional interpretation capabilities [9]. As AI technologies evolve, their role in transforming healthcare practices and improving patient outcomes remains crucial, driving medical innovation.

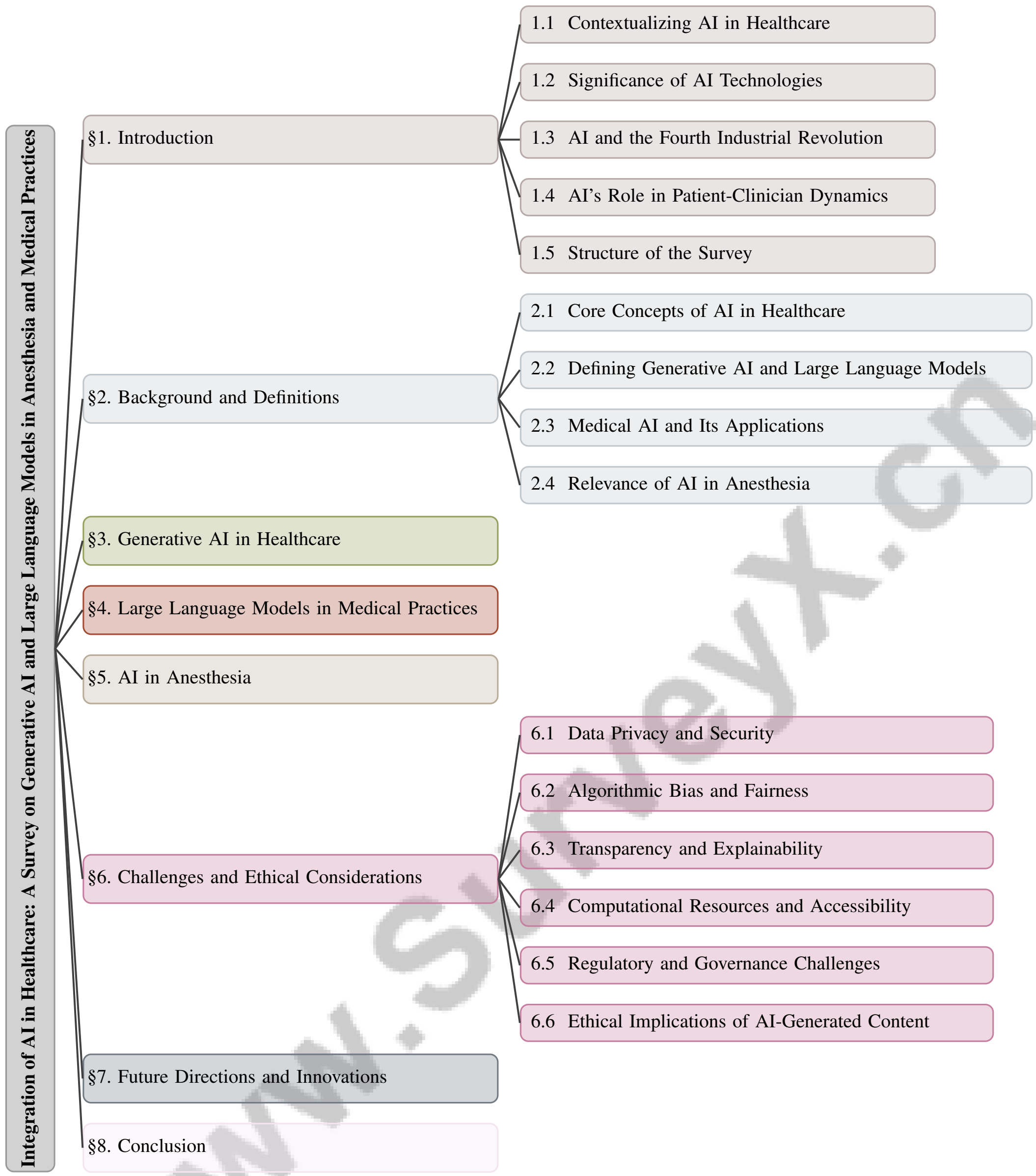

Figure 1: chapter structure

1.2 Significance of AI Technologies

The integration of AI technologies into modern medical practices marks a transformative shift, significantly enhancing patient care, diagnosis, and treatment planning. AI facilitates the creation of persuasive health messages, crucial for improving patient engagement and education, particularly in oncology [10]. In cardiology, the synergy of AI with Extended Reality (XR) technologies has led to substantial improvements in diagnostics and treatment planning, resulting in enhanced patient outcomes [11]. Furthermore, AI's application in early detection, monitoring, and disease prevention emphasizes its potential to proactively manage health conditions [12].

AI technologies are pivotal in combating misinformation in healthcare, as exemplified by the WashKaro mobile health application, which promotes informed health decisions through reliable information dissemination [13]. In pathology, standardization, interoperability, and explainability are essential for effective AI implementation in clinical settings [14]. The importance of explainable AI (xAI) is particularly evident in mental health diagnostics, where it enhances trust in AI systems, as shown by the Logical Neural Network (LNN) [5]. Additionally, integrating physiological data

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into LLMs aims to create empathic chatbots capable of recognizing users' emotional states, thereby improving patient-clinician interactions [9].

AI's potential to enhance decision-making processes and organizational governance in healthcare is increasingly recognized, emphasizing its role in improving healthcare delivery efficiency [15]. The democratization of AI necessitates user-friendly systems capable of managing complex biomedical data, broadening access to AI's benefits [16]. In Human-Computer Interaction (HCI), developing effective interfaces for generative AI models is crucial for impactful medical applications [17].

Significant advancements are also evident in AI's application to continuous imagined speech decoding, as demonstrated by the MindSpeech model, which enhances human-AI interaction [18]. The potential of AI chatbots to provide personalized cognitive training experiences further illustrates AI's adaptability to individual user needs [19]. Additionally, the integration of quantum machine learning (QML) for efficient signal processing marks a notable advancement, leveraging quantum computing's capabilities [20]. Collectively, these developments underscore the critical importance of AI technologies in revolutionizing medical practices and enhancing patient care. The integration of IoT data with clinical records creates actionable insights for improved health outcomes, emphasizing the need for innovative methodologies for early detection and proactive prevention, particularly in light of challenges posed by the COVID-19 pandemic. The proposed LLM-Assisted Inference aims to streamline understanding and explanation of key decision factors, further enhancing decision-making processes in healthcare [21].

1.3 AI and the Fourth Industrial Revolution

The Fourth Industrial Revolution is characterized by the convergence of advanced technologies, including artificial intelligence (AI), fundamentally altering industries and societal structures. AI leads this transformation, reshaping business operations and decision-making processes through more efficient management practices [22]. In healthcare, AI's implications are profound, offering innovative solutions that enhance patient outcomes via improved diagnostics, treatment personalization, and operational efficiencies.

The integration of AI with edge computing is a crucial aspect of the Fourth Industrial Revolution, particularly in healthcare settings requiring real-time data processing. This synergy enables AI applications that necessitate immediate data analysis and response, such as patient monitoring systems and emergency diagnostics [23]. Addressing challenges associated with deploying AI at the edge, including data privacy, security, and computational constraints, is vital for healthcare systems to fully leverage AI technologies.

As AI evolves within the Fourth Industrial Revolution, its role in healthcare extends beyond traditional applications, fostering a more interconnected and responsive healthcare ecosystem. The rapid advancement of AI necessitates a comprehensive reevaluation of existing healthcare models to effectively integrate AI-driven insights, transforming technological advancements into measurable improvements in patient care and healthcare delivery systems. As patients gain access to advanced machine learning tools for diagnosis and recommendations, the dynamics of patient-clinician relationships are changing, requiring new workflows and skills. Furthermore, the governance surrounding AI adoption in healthcare remains inadequately defined, highlighting the necessity for health system leaders to establish clear standards and decision-making processes to facilitate the responsible and effective use of AI technologies [15, 24].

1.4 AI's Role in Patient-Clinician Dynamics

The integration of artificial intelligence (AI) into healthcare is fundamentally transforming patient-clinician dynamics, enhancing communication and decision-making processes. AI's automation of diagnosis and monitoring significantly alleviates healthcare workers' workloads, enabling them to concentrate more on patient interaction and care [12]. This automation streamlines clinical workflows and facilitates more timely and efficient patient management.

The emergence of explainable AI (xAI) is critical in bridging the gap between AI systems and healthcare professionals. By providing transparency into AI decision-making processes, xAI allows domain experts to validate AI predictions, thereby enhancing trust and facilitating informed decision-making [25]. Incorporating causal explanations into xAI frameworks further strengthens trust by clarifying the reasons behind AI model outputs, essential for fostering collaborative human-AI interactions [26].

The transformation in patient-clinician relationships is also propelled by the increasing accessibility of AI-based medical advice. The 'Bring Your Own Algorithm' (BYOA) phenomenon empowers patients to access and introduce AI-generated insights into clinical consultations, influencing treatment discussions and decisions [24]. This shift necessitates a reevaluation of traditional patient-clinician dynamics, as clinicians must adapt to a more informed patient base actively participating in their healthcare journeys.

Moreover, the explainability of AI systems is crucial in shaping user trust and understanding within healthcare settings. Different explanation styles significantly impact how end-users perceive and interact with AI technologies, underscoring the need for tailored communication strategies that accommodate diverse user preferences and comprehension levels [27]. By enhancing the transparency and interpretability of AI systems, healthcare providers can ensure the effective integration of AI-driven insights into clinical practice, ultimately improving patient outcomes and satisfaction.

1.5 Structure of the Survey

This survey is structured to provide a comprehensive exploration of the integration of artificial intelligence (AI) technologies, specifically generative AI and large language models (LLMs), into the healthcare sector, with a focus on anesthesia and medical practices. It begins with an introduction that establishes the significance of AI technologies in modern medical practices and their transformative potential in enhancing patient care. Following this, a background and definitions section elaborates on core concepts of AI in healthcare, providing clear definitions of key terms such as generative AI, large language models, and medical AI.

The survey then examines the applications of generative AI in healthcare, highlighting its role in synthetic data generation, diagnostic enhancement, and personalized treatment planning. The discussion is enriched by an analysis of LLMs in medical practices, emphasizing their advanced capabilities in processing medical information and enhancing clinical decision-making. This includes the development of specialized models like Medical mT5 and GatorTron, which utilize extensive multilingual corpora and large-scale clinical data to improve the accuracy of tasks such as clinical concept extraction and treatment recommendations. Benchmarks like CLIBENCH provide a comprehensive evaluation of LLMs' effectiveness across diverse medical scenarios, underscoring their potential to transform patient-specific decision-making in real-world healthcare settings [28, 29, 30, 31, 32].

A dedicated section on AI in anesthesia explores specific applications such as patient monitoring, outcome prediction, and delivery optimization, showcasing the critical impact of AI technologies in this specialized field. The survey also addresses challenges and ethical considerations associated with AI in healthcare, including data privacy, algorithmic bias, and the need for transparency and explainability.

In conclusion, the paper discusses prospective avenues and innovations in AI-driven healthcare, highlighting emerging trends such as the integration of psychological and social data into medical understanding, the necessity for robust organizational governance frameworks for AI adoption, and the potential of advanced AI technologies like LLMs to enhance patient-provider communication. It underscores the critical role of collaborative research efforts among healthcare leaders, technologists, and social scientists in advancing the effective implementation of AI technologies across various medical domains, ultimately aiming to improve patient outcomes and healthcare delivery [15, 2, 10]. Through this structured approach, the survey aims to provide a holistic understanding of the current state and future potential of AI in transforming healthcare practices.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Core Concepts of AI in Healthcare

AI's integration into healthcare leverages machine learning and deep learning to enhance perception, reasoning, and decision-making, significantly impacting medical imaging and complex condition analysis. AI models improve interpretations of Chest X-rays and address open-set recognition challenges, maintaining accuracy by rejecting unknown classes [33]. Large language models (LLMs) are vital for text generation and natural language understanding, processing extensive datasets to refine diagnostics and decision-making [32]. Optimization algorithms further bolster LLMs' decision-making, though class imbalance and data heterogeneity remain challenges [34].

Multi-modal data processing amplifies AI's potential, integrating diverse sources for diagnostic accuracy and treatment personalization [7]. Explainability fosters trust, influencing user interactions with mobile health applications [27]. AI's application in supervised learning and deep learning for conditions like schizophrenia underscores its transformative role in patient care and operational efficiency [6].

2.2 Defining Generative AI and Large Language Models

Generative AI and LLMs are pivotal in healthcare, addressing data scarcity and enhancing medical communication. Generative AI, through models like GANs and VAEs, creates synthetic data crucial for training AI models in scenarios with limited real data, facilitating robust datasets for research and diagnostics [35]. Synthetic medical images enhance diagnostic tool interpretability and expand training datasets [7]. LLMs, such as GatorTron, process and generate language, aiding complex tasks in healthcare [29]. They enhance clinical decision-making by improving medical information retrieval and analysis [9]. Ensuring LLM robustness and reliability while preventing harmful or biased content generation is crucial [36].

Integrating LLMs with neuro-symbolic architectures, like Logical Neural Networks (LNN), enhances reasoning for sophisticated decision-making [5]. Specialized models tailored for medical tasks improve diagnostic accuracy and facilitate patient-clinician interactions [32]. Continuous evaluation and refinement of generative AI and LLMs are essential for successful healthcare integration, improving patient outcomes and addressing data quality, size, and bias challenges [37].

2.3 Medical AI and Its Applications

AI applications in medicine enhance diagnostic accuracy, treatment personalization, and healthcare delivery. AI advances medical imaging, improving segmentation and interpretation, as seen in fetal brain segmentation and PET imaging [38]. GANs generate synthetic lung CT scans and X-ray images, aiding COVID-19 diagnosis by creating robust datasets [39]. Addressing generative AI hallucinations is crucial for fostering trust and adoption [37].

AI enhances mental health management by monitoring symptoms, predicting relapse risks, and aiding schizophrenia rehabilitation [6]. A framework for improving mortality risk prediction using EHR data demonstrates AI's prognostic accuracy [34]. LLMs like GatorTron advance clinical NLP, outperforming existing models and enhancing decision-making [29]. AI4COVID-19, analyzing cough sounds for diagnosis, highlights AI's adaptability in emergent healthcare challenges [40].

AI democratization is evident in systems like PennAI, automating machine learning analyses for complex biomedical data [16]. AI in clinical trials, exemplified by AICO, enhances trial generalizability, facilitating patient enrollment [41]. Addressing AI bias is crucial to prevent reinforcing inequalities [42]. CLIBENCH evaluates LLMs in clinical diagnosis, highlighting the need for understanding medical LLM limitations in real-world applications [28, 36]. These applications underscore AI's transformative potential in revolutionizing medical practices and enhancing patient care.

2.4 Relevance of AI in Anesthesia

AI's integration in anesthesia enhances patient safety, optimizes medication dosing, and improves clinical outcomes. AI's ability to manage complex datasets and adapt to context-sensitive environments suits anesthesia, where precise monitoring and rapid decision-making are essential [23]. Models like StratMed address medication recommendation challenges by balancing safety and accuracy against the long-tail distribution of medical data [43]. AI improves diagnostic accuracy and interpretative reliability, crucial in anesthesia [44]. The concept of 'superminds' illustrates AI's role in augmenting human capabilities in strategic decision-making [22]. Advancements in medical imaging, like MedImageInsight, facilitate task generalization, reducing the need for separate models [45].

Data privacy and regulatory compliance challenges are relevant in anesthesia due to patient data sensitivity [1]. AI's ability to navigate these challenges while ensuring compliance and addressing ethical implications is crucial [46]. The importance of diverse datasets for AI applications in healthcare emphasizes the need for robust data frameworks [47]. AI in anesthesia improves patient outcomes through advanced monitoring, accurate medication delivery, and streamlined decision-making, aligning with broader healthcare trends [46, 10, 24].

3 Generative AI in Healthcare

Category	Feature	Method
Synthetic Data Generation	Model Parameter Adjustment	MS[8]
Enhancing Diagnostic Processes	Radiology and Sound Analysis Data Integration and Hypothesis	AI4COVID[40], R3[48] BRAINSTORM[49], EmLLM[9]
Personalized Treatment Plans	Data-Driven Personalization Cognitive Enhancement Strategies Advanced Signal Processing	LAI[21], SM[43] NE[50], ReMe[19] QNN[20]
Innovative Applications and Case Studies	Data Manipulation Techniques Automation in Healthcare Synthetic Data Applications	SGIM[51], DRAGON-AI[52] PF[53], AICO[41] SinGAN[54]

Table 1: This table presents a comprehensive summary of various methods and applications of generative AI in healthcare, categorized into synthetic data generation, diagnostic process enhancement, personalized treatment plans, and innovative applications. It highlights key features and methods employed within each category, showcasing the diverse strategies and technologies utilized to advance healthcare outcomes through AI-driven solutions.

The integration of Generative Artificial Intelligence (AI) in healthcare has spurred significant advancements, particularly in data utilization and clinical outcomes enhancement. Table 1 provides an organized overview of the methods and applications of generative AI in healthcare, illustrating the breadth of its impact across different domains. Additionally, Table 3 presents a detailed comparison of the primary functions, key technologies, and unique advantages of various generative AI applications in healthcare. This section explores generative AI's multifaceted applications, starting with synthetic data generation. Synthetic datasets mitigate the challenges of limited real-world medical data access and protect patient privacy, facilitating robust medical model development. Subsequent discussions focus on methodologies and implications of synthetic data generation in healthcare innovation.

3.1 Synthetic Data Generation

Generative AI is crucial for creating synthetic data, essential for training medical models where real data is scarce or sensitive. Advanced generative models enable synthetic patient data generation, addressing privacy concerns while providing data-driven insights, especially in specialized domains facing data scarcity [3]. The fusion of quantum neural networks with classical deep networks in frameworks like QueegNet exemplifies enhanced physiological data processing, contributing to high-quality synthetic datasets [3]. Techniques like Model Surgery refine data generation by editing language model parameters, ensuring synthetic data aligns with desired outcomes [8]. Frameworks such as AICO use transformer-based NLP to extract clinical trial eligibility criteria, enhancing synthetic dataset quality and applicability [41]. These advancements significantly improve medical model training and testing, leading to better healthcare outcomes.

3.2 Enhancing Diagnostic Processes

Generative AI enhances diagnostic accuracy and efficiency across medical domains. Large Language Models (LLMs) integrated with architectures like RadPhi-3 streamline radiology diagnostics by performing tasks such as impression summarization, increasing precision and speed [48]. In oncology, Specific Instance Learning (SIL) surpasses Multiple Instance Learning (MIL) in oral cancer detection, demonstrating the importance of customized AI strategies [55]. The AI4COVID-19 method uses machine learning to analyze cough sounds, improving diagnostic accuracy for infectious diseases [40]. Innovations like BRAINSTORM reduce confirmation bias by generating less likely hypotheses, enhancing diagnostic accuracy [49]. In dermatology, the PanDerm model integrates multi-modal data for improved diagnostic accuracy [56]. Tools like the EmLLM chatbot predict user stress, enhancing digital mental health diagnostics [9]. Despite these advancements, challenges such as encoding ambiguities in Multi-Modal Large Language Models (MLLMs) highlight the need for reliable

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AI systems in clinical settings [36]. Collectively, these innovations demonstrate generative AI's transformative impact on diagnostics, improving accuracy, efficiency, and accessibility in healthcare.

3.3 Personalized Treatment Plans

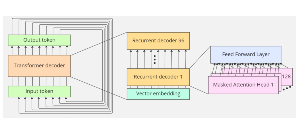
Generative AI is pivotal in crafting personalized treatment strategies, tailoring healthcare solutions to individual needs. Neural erosion methods emulate cognitive decline, providing frameworks for understanding and mitigating neurodegenerative processes through personalized interventions [50]. StratMed's stratification strategy balances safety and accuracy in medication recommendations, optimizing therapeutic outcomes [43]. The ReMe application develops personalized cognitive training for older adults, enhancing memory and cognitive function [19]. The HELPERT benchmark evaluates LLMs in delivering Cognitive Behavioral Therapy (CBT), facilitating personalized psychological interventions [57]. Quantum AI models like quEEGNet handle complex biosignal data, essential for responsive personalized treatment plans [20]. LLMs enhance decision-making processes by interpreting optimized solutions, aligning treatment strategies with patient preferences [21]. These advancements underscore generative AI's role in revolutionizing personalized treatment, improving patient outcomes and satisfaction. Generative models also address annotation shifts in cancer classification, enhancing diagnostic accuracy with minimal data input [54, 58, 24].

3.4 Innovative Applications and Case Studies

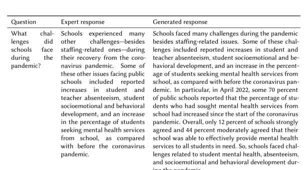
Method Name	Application Domains	Technological Integration	Operational Impact
SGIM[51]	Medical Imaging	Transformer Recurrent Decoder	Diagnostic Precision
SinGAN[54]	Breast Cancer Classification	Multi-scale Generative	Improved Classification Performance
AICO[41]	Clinical Trials	Transformer-based Nlp	Improve Trial Generalizability
PF[53]	-	Transformer Recurrent Decoder	Diagnostic Precision
DRAGON-AI[52]	Ontology Engineering	Retrieval Augmented Generation	Reducing Manual Effort

Table 2: Table illustrating various generative AI methods applied in medical contexts, highlighting their application domains, technological integrations, and operational impacts. The table provides a comprehensive overview of how these methods enhance diagnostic precision, improve classification performance, and reduce manual effort in diverse healthcare scenarios.

Generative AI's transformative potential is evident in various innovative applications and case studies across medical domains. StyleGAN-based methods in medical imaging enhance black-box model prediction interpretability, increasing trust in AI predictions [51]. The interplay between Human-Computer Interaction (HCI) and generative models creates intuitive interfaces for medical applications, facilitating AI integration in healthcare [17]. High-quality synthetic images mitigate annotation shifts in oncology, improving model robustness [54]. The AICO framework automates clinical trial eligibility extraction, enhancing trial design scalability and efficiency [41]. PlanFitting generates personalized exercise plans, promoting health and wellness [53]. Dynamic retrieval-augmented generation techniques improve ontology editing workflows, enhancing data management tasks [52]. These case studies demonstrate generative AI's effective application in diverse medical contexts, enhancing diagnostic precision, facilitating personalized treatment strategies, and boosting operational efficiency by addressing data scarcity and annotation challenges [39, 2, 58, 54]. Table 2 provides a detailed examination of the innovative applications of generative AI methods in medical domains, showcasing their technological integration and operational impact.

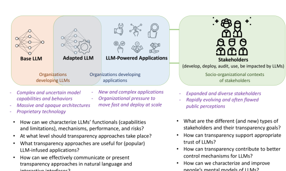


(a) Transformer Recurrent Decoder Architecture[59]



Question	Expert response	Generated response
What challenges did schools face during the pandemic?	Schools experienced many other challenges—besides staffing-related ones—during their recovery from the coronavirus pandemic. Some of these other issues facing public schools included reported increases in student and teacher absenteeism, student socioemotional and behavioral development, and an increase in the percentage of students seeking mental health services from school, as compared with before the coronavirus pandemic.	Schools faced many challenges during the pandemic besides staffing-related issues. Some of these challenges included reported increases in student and teacher absenteeism, student socioemotional and behavioral development, and an increase in the percentage of students seeking mental health services from school, as compared with before the coronavirus pandemic. In particular, in April 2022, some 70 percent of public schools reported that the percentage of students who had sought mental health services from school had increased since the start of the coronavirus pandemic. Overall, only 12 percent of schools strongly agreed and 44 percent moderately agreed that their school was able to effectively provide mental health services to all students in need. So, schools faced challenges related to student mental health, absenteeism, and socioemotional and behavioral development during the pandemic.

(b) Schools faced many challenges during the pandemic besides staffing-related issues[60]



(c) Transparency in the Era of Large Language Models: Challenges and Opportunities[61]

Figure 2: Examples of Innovative Applications and Case Studies

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As shown in Figure 2, generative AI is making significant strides in healthcare through innovative solutions and transformative applications. The "Transformer Recurrent Decoder Architecture" illustrates an advanced AI architecture that enhances complex data processing and generation. This architecture is crucial for developing sophisticated AI models that interpret and generate medical data accurately. The challenges faced by schools during the pandemic highlight AI's broader implications in addressing systemic problems through data-driven insights, contributing to strategic decision-making in healthcare education and management. The discussion on "Transparency in the Era of Large Language Models" emphasizes the need for transparency and accountability in AI deployment, highlighting ethical considerations and opportunities for enhancing trust in healthcare AI applications. These examples collectively underscore generative AI's transformative potential in revolutionizing healthcare through innovative applications and case studies [59, 60, 61].

Feature	Synthetic Data Generation	Enhancing Diagnostic Processes	Personalized Treatment Plans
Primary Function	Data Creation	Diagnostic Accuracy	Personalized Healthcare
Key Technology	Quantum Neural Networks	Large Language Models	Quantum AI Models
Unique Advantage	Privacy Protection	Increased Precision	Tailored Interventions

Table 3: The table provides a comparative analysis of three generative AI applications in healthcare: synthetic data generation, enhancing diagnostic processes, and personalized treatment plans. It highlights the primary function, key technology, and unique advantage of each application, showcasing their distinct contributions to advancing healthcare practices.

4 Large Language Models in Medical Practices

4.1 Capabilities of Large Language Models in Medical Information Processing

Large Language Models (LLMs) have transformed medical information processing by adeptly managing complex linguistic and logical tasks. OncoGPT, for example, utilizes a specialized dataset to enhance oncology-specific information processing, providing precise insights crucial for clinical decision-making [62]. The MRKL method showcases the integration of neural networks with symbolic reasoning, facilitating nuanced interpretations of medical data [63].

The geometric properties of multi-head attention (MHA) within LLMs illuminate their internal processing, crucial for effective medical content generation [64]. Categorizing foundation models into sub-fields like language, vision, and bioinformatics underscores LLMs' diverse applications in healthcare challenges [65]. GatorTron, leveraging transformer architecture, excels in extracting insights from clinical narratives, aiding healthcare professionals in deriving actionable information from unstructured data [29]. LLMs streamline pharmaceutical operations and enhance healthcare solutions' accuracy and context sensitivity, addressing issues like hallucination and ethical concerns. These models facilitate domain-specific applications, including chatbots, emphasizing the need for rigorous evaluation to ensure output reliability and transparency. Consequently, LLMs are poised to transform healthcare delivery by offering precise, efficient, and ethically sound solutions tailored to medical practice complexities [66, 46, 61, 60, 67].

4.2 Specialized Large Language Models for Medical Applications

The development of specialized Large Language Models (LLMs) for medical applications marks a significant advancement in natural language processing (NLP) within healthcare. These models address clinical text's unique challenges, characterized by complex terminology and intricate relationships. GatorTron exemplifies how larger models trained on extensive datasets capture nuanced patterns in clinical narratives, enhancing tasks like entity recognition and clinical note summarization [29].

Specialized LLMs improve medical language understanding, refining information extraction processes critical for clinical decision-making, ensuring healthcare professionals receive accurate, timely information essential for diagnosis and treatment. Automated clinical coding transforms medical records into structured data, supporting evidence-based practices, while advanced machine learning tools enhance patient-generated data interpretation, improving patient-clinician interactions [68, 2, 24]. Tailoring LLM architectures to medical contexts provides actionable insights that enhance patient care and operational efficiency.

Specialized LLMs' adaptability across healthcare sub-fields, such as oncology and cardiology, underscores their versatility. Domain-specific models like Medical mT5, SMP-BERT, OncoGPT, GatorTron, and Sporo AraSum improve response precision in medical fields, addressing challenges like language diversity and data imbalance. Medical mT5 supports multiple languages through a large multilingual corpus, SMP-BERT employs prompt learning for low-resource languages, OncoGPT enhances oncology inquiries, and GatorTron processes unstructured electronic health records. Sporo AraSum excels in Arabic clinical documentation, ensuring culturally sensitive communication. These advancements foster effective interactions in diverse healthcare settings [69, 29, 30, 31, 62]. The continuous evolution of specialized LLMs is crucial for advancing their capabilities, ensuring effective integration into diverse medical applications, and driving innovation to improve healthcare outcomes.

4.3 Integration of Multi-Modal Data in Medical Practices

The integration of multi-modal data in medical practices represents a transformative advancement enabled by Large Language Models (LLMs), proficient in synthesizing diverse data types to enhance healthcare delivery. Multi-modal models, particularly those employing transformer architecture, excel in processing complex datasets, including textual, visual, and physiological information, supporting comprehensive clinical decision-making [29].

By integrating data from various sources, such as medical images and clinical notes, multi-modal LLMs facilitate holistic patient assessments, improving diagnostic accuracy and treatment personalization [7]. Their ability to incorporate domain-specific knowledge, including medical terminologies and clinical guidelines, enriches interpretative accuracy and contextual relevance [29].

The integration of multi-modal data fosters the development of intuitive healthcare applications, such as digital health assistants and diagnostic tools, dynamically adapting to healthcare providers' and patients' needs. Leveraging LLM capabilities to synthesize diverse data streams, these applications deliver timely insights and tailored recommendations, streamlining clinical workflows and significantly improving patient outcomes. Comprehensive evaluation benchmarks, like CLIBENCH, emphasize the importance of assessing LLM performance across clinical tasks, enhancing LLM-powered healthcare solutions' reliability and effectiveness [60, 28, 61].

The ongoing evolution of multi-modal LLMs highlights their potential to revolutionize medical practices by providing comprehensive patient health insights and facilitating effective healthcare solutions. As healthcare foundation models (HFMs) advance, their integration into clinical settings is expected to enhance medical care quality and accessibility by optimizing diverse healthcare data utilization, improving patient-clinician interactions through advanced AI tools, and enabling efficient processing of unstructured electronic health records (EHRs). These developments promise to streamline healthcare delivery and transform patient engagement and medical information interpretation dynamics [29, 65, 2, 24].

5 AI in Anesthesia

AI is transforming anesthesia by enhancing precision in procedures and improving patient safety and outcomes. This section examines AI's multifaceted roles in anesthesia, starting with patient vital monitoring.

5.1 Monitoring Patient Vitals

AI has revolutionized monitoring patient vitals during anesthesia, enhancing safety and optimizing care through efficient real-time data processing in dynamic surgical settings. Systems like the Logical Neural Network (LNN) offer interpretable insights, aiding diagnostics and decision-making [5]. AI improves data classification and retrieval, crucial for swiftly addressing surgical complications. IoT integration allows continuous, non-invasive vital sign monitoring, enabling proactive patient care and long-term health management strategies [70, 71, 2, 72, 73]. Continuous remote monitoring equips anesthesiologists with valuable insights, enhancing decision-making and outcomes.

AI's adaptability in clinical settings is vital for maintaining high care standards, minimizing adverse events, and improving anesthetic administration efficiency. Continuous data collection from IoT devices and sophisticated algorithms analyze this alongside clinical records and behavioral insights, providing actionable information for timely interventions and personalized health management [15, 72, 4]. Advanced AI models ensure continuous patient vital monitoring, contributing to medical practice advancements through real-time insights.

5.2 Predicting Anesthesia Outcomes

AI enhances anesthesia outcome prediction and complication anticipation, improving clinical decision-making. Technologies like OncoGPT accurately predict outcomes and respond to complex inquiries, highlighting their anesthesia significance [62]. SMP-BERT manages imbalanced datasets, ensuring high performance with limited data, allowing accurate anesthesia risk predictions [30]. AI models address real-world complexities, offering anesthesiologists insights that improve patient management and safety.

Benchmarks like CLIBENCH ensure AI models enhance clinical decision-making accuracy in anesthesia outcomes [28]. Brainstorming frameworks reduce missed diagnoses, improving anesthesia outcome prediction [49]. Open-set recognition challenges in medical imaging necessitate tailored approaches for anesthesia outcome prediction [33]. AI processes complex data, manages imbalances, and provides reliable insights, enhancing patient care and safety in anesthesia.

5.3 Optimizing Anesthesia Delivery

AI significantly optimizes anesthesia delivery, enhancing safety and outcomes. Systems like the M3OE module enable adaptive expert system selection, crucial for precise dosing and delivery [74]. LLMs optimize anesthesia delivery by refining dosing strategies, ensuring safe, effective administration tailored to individual needs [32].

The SUGAR network optimizes diagnostic imaging, enhancing pre-operative assessments by improving CT image quality and minimizing radiation exposure [38]. High-quality imaging data enables precise anesthesiologist decision-making. MMLLMs generate treatment plans by synthesizing diverse data inputs [7], optimizing anesthesia delivery by considering various physiological and clinical parameters.

AI's role in optimizing anesthesia delivery is transformative, adapting to complex scenarios, enhancing algorithm design, and integrating diverse data inputs. This streamlines anesthetic practices and improves safety and outcomes. Advanced machine learning techniques analyze real-time data and surgical behaviors, facilitating precise anesthesia management tailored to individual needs. Explainable AI systems enhance communication between providers and patients, ensuring that clinical decisions are transparent and informed by AI insights and human expertise [25, 10, 24, 46, 73].

5.4 Reducing Healthcare Worker Workload

AI reduces healthcare worker workload in anesthesia through automation and enhanced decision support systems. Automated clinical coding alleviates administrative burdens, streamlining data entry and classification, allowing professionals to focus on direct patient care [68]. Models like MindSpeech offer non-invasive communication interfaces, transforming patient interactions and reducing workload [18].

AI-driven energy-efficient models optimize resource utilization, reducing operational costs in resource-constrained settings [75]. Federated Learning (FFL) facilitates collaborative model training using heterogeneous datasets without uniform labeling, reducing data preprocessing needs [76].

Challenges in AI technology adoption include slow adoption rates, data privacy issues, and complex regulatory requirements, hindering workload reduction potential [14]. The complexity and costs of advanced digital nucleic acid amplification tests (dNAAT) require specialized training, complicating workflow integration [77].

Despite challenges, integrating genomic, environmental, and zoonotic data in AI models enhances predictive accuracy, aiding healthcare workers in informed decision-making [78]. IoT and AI integration streamlines data collection and improves monitoring, though it requires careful data integration and privacy consideration [72].

6 Challenges and Ethical Considerations

Incorporating artificial intelligence (AI) into healthcare involves navigating significant challenges and ethical considerations. Data privacy and security are critical, affecting both the operational success of AI systems and patient trust. The following subsections explore the complexities of data privacy and security, algorithmic bias and fairness, transparency and explainability, computational resources and accessibility, regulatory and governance challenges, and the ethical implications of AI-generated content.

6.1 Data Privacy and Security

Ensuring data privacy and security is crucial for AI deployment in healthcare, especially under regulations like HIPAA and GDPR. Techniques such as federated learning allow AI model training across multiple sites without compromising patient privacy, fostering robust AI development [7]. The integration of AI and IoT technologies heightens data privacy risks, necessitating stringent measures to prevent re-identification and ensure data validation in rare medical imaging scenarios [33].

In radiology, minimizing radiation exposure while maintaining data security is vital. Tools like MedImageInsight demonstrate the dual challenge of utilizing medical data for research while safeguarding confidentiality [79, 80, 45, 4]. Privacy breaches, such as membership inference attacks, highlight the need for privacy-preserving AI techniques. Although synthetic data can address data scarcity, it may not reflect real-world complexities.

Ethical considerations are integral, especially for LLMs, which face challenges like hallucination and accountability. Post-processing layers that inform users of potentially fabricated outputs enhance transparency and align with ethical frameworks advocating responsible AI development [81, 67, 61]. This focus is crucial in mental health AI applications. Balancing advanced machine learning with privacy-preserving methods is essential, given the sensitive nature of medical data. As healthcare transitions to a "Bring Your Own Algorithm" era, evolving patient-clinician dynamics necessitate an approach that respects ethical standards and privacy [68, 82, 4, 24, 2].

6.2 Algorithmic Bias and Fairness

Algorithmic bias in AI systems poses significant challenges in healthcare, potentially leading to treatment disparities. The SUGAR method's training data quality affects AI model generalizability, raising bias concerns [38]. Similarly, Logical Neural Network (LNN) methods' predicate specificity may contribute to misdiagnosis, emphasizing fairness [5].

Challenges in ensuring data quality and diversity, particularly in GAN-based methods, include data bias and reproducibility issues, hindering clinical acceptance [39]. Inconsistent terminology across fields complicates collaboration [35]. Models like CT-BERT risk bias by overlooking unique trial eligibility criteria, affecting clinical decisions [41]. The opaque nature of many AI systems can erode trust among end-users, hindering practical applications [27].

Addressing bias and fairness requires robust evaluation frameworks and model refinement to ensure equitable outcomes. Privacy-preserving AI techniques, such as federated learning and synthetic data, and interdisciplinary collaboration can reduce care disparities, enhancing reliable AI applications [82, 4, 58, 2, 72].

6.3 Transparency and Explainability

Transparency and explainability are crucial for AI deployment in healthcare, building trust among clinicians and patients. Deep learning models' black-box nature raises interpretability concerns, essential for reliable AI-driven healthcare decisions [83]. This is particularly important in mental health, where understanding AI predictions informs decisions [26].

AI integration into patient-clinician interactions presents opportunities and challenges, requiring a balance between AI benefits and maintaining trust [24]. Tailored ethical frameworks for LLMs and dynamic auditing systems ensure transparency and accountability [67].

Efforts to enhance transparency include organizing AI methods into reasoning, decision-making, and learning techniques, facilitating clearer understanding and compliance with security regulations [84,

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4]. Standardizing medical AI terminology enhances clarity and fosters interdisciplinary collaboration [35]. Privacy-preserving techniques, such as global differential privacy, safeguard patient privacy while maintaining diagnostic accuracy [1].

Enhancing transparency and explainability fosters trust in healthcare AI, ensuring AI-driven decisions are reliable and interpretable. Human-centered transparency approaches allow stakeholders to understand AI processes and outcomes better. Explainable AI improves task performance in human-AI collaborations, enabling experts to validate predictions. Effective governance is crucial for responsible AI adoption, guiding leaders through integration complexities. Prioritizing transparency will facilitate informed decision-making and enhance AI efficacy in healthcare [25, 15, 2, 61]. Ongoing interdisciplinary dialogue and ethical frameworks are necessary to navigate AI challenges in clinical settings.

6.4 Computational Resources and Accessibility

AI integration in healthcare faces challenges related to computational resources and accessibility, affecting AI solution adoption. High computational costs for training and deploying LLMs limit access for underfunded research labs, restricting AI advancements [32]. Integrating AI systems into clinical workflows is complex, compounded by limited high-quality datasets [6].

Quantum Neural Networks (QNNs) face hurdles due to ideal simulator reliance, raising practical application concerns in resource-limited scenarios. Increasing patient populations necessitate rapid decision-making technologies, yet current infrastructure may not efficiently meet demands [9].

Automated clinical coding complexity and costs limit usage in resource-constrained settings. High costs of digital nucleic acid amplification tests (dNAAT), including advanced technologies like dPCR and dLAMP, hinder accessibility in economically disadvantaged regions. Despite offering superior diagnostic capabilities, substantial equipment and training investments are required. AI integration has yet to bridge affordability and usability gaps, limiting adoption of transformative diagnostic tools [68, 85, 77].

Developing AI applications highlights selection bias and missing data challenges, compounded by computational resource demands. Enhancing app features while ensuring privacy requires substantial resources, limiting effective AI solution development and deployment [80].

Addressing computational resource and accessibility challenges is essential for AI integration in healthcare. Enhancing governance and decision-making processes ensures diverse healthcare practices benefit from AI while maintaining stakeholder transparency and understanding [15, 2, 65, 61]. Strategic infrastructure investments, cost-effective solutions, and equitable access are necessary to realize AI benefits across diverse healthcare settings.

6.5 Regulatory and Governance Challenges

AI integration in healthcare faces regulatory and governance challenges affecting adoption and efficacy. Implementing advanced technologies like blockchain and federated learning requires robust regulatory frameworks to address unique demands [86]. These technologies promise enhanced data security and collaborative research but pose hurdles related to privacy laws like GDPR and privacy-preserving techniques [82].

The absence of standardized governance frameworks exacerbates AI adoption challenges, leading to inefficiencies and risks [15]. Trust in AI systems, compounded by regulatory hurdles, remains a significant barrier to implementation [47]. Managing edge infrastructure for AI deployment complicates compliance, necessitating comprehensive governance strategies [23].

Future research should prioritize AI integration into clinical workflows, focusing on robust validation datasets and addressing regulatory challenges to facilitate broader adoption [14]. Enhancing multi-modal large language models' (MLLMs) visual reasoning capabilities and developing comprehensive benchmarks, as highlighted in the MediConfusion study, are essential [36]. Addressing regulatory and governance challenges enables healthcare systems to leverage AI technologies for improved patient outcomes and operational efficiencies.

6.6 Ethical Implications of AI-Generated Content

The ethical implications of AI-generated content in healthcare involve interpretability, fairness, and trust issues. Ensuring AI system reliability and safety requires rigorous testing before clinical application, emphasizing thorough evaluation of proposed methods [49]. In mental health, ethical LLM use is a significant concern, highlighting responsible AI deployment in therapeutic settings [57].

Maintaining fairness in AI-generated content is critical, particularly in addressing biases from homogenization and lack of diversity. Improving human-AI interactions can mitigate these risks, allowing personalized outputs that preserve diversity while achieving productivity gains [42]. This ensures AI systems cater to diverse demographic needs, promoting equitable medical application outcomes.

Privacy concerns are paramount in ethical AI deployment. Future research should focus on novel anonymization techniques and leveraging technologies like federated learning and blockchain to enhance privacy while facilitating data sharing [80]. This is crucial for safeguarding patient information and maintaining AI system trust.

Ethical analysis of AI applications, such as facial recognition in medicine, illustrates practical ethical framework application and highlights potential biases and privacy concerns [81]. Refining interactive explanation designs is necessary to address privacy concerns while enhancing user engagement with AI systems [27].

7 Future Directions and Innovations

The rapid evolution of artificial intelligence (AI) in healthcare presents opportunities and challenges that necessitate a forward-looking approach. This section explores future directions and innovations, focusing on enhancing model capabilities and operational efficiency, and highlights specific advancements and research initiatives paving the way for effective AI applications in healthcare. Figure 3 illustrates these future directions and innovations in AI for healthcare, emphasizing key areas such as the enhancement of model capabilities and efficiency, the integration of AI across diverse medical domains, and the development of innovative AI-driven healthcare solutions. Furthermore, the figure underscores the importance of collaborative and interdisciplinary research efforts. Each category within the figure is detailed with specific advancements and research initiatives aimed at improving patient care, operational efficiencies, and ethical standards in the rapidly evolving field of AI in healthcare.

7.1 Enhancing AI Model Capabilities and Efficiency

Research is increasingly focused on enhancing AI model capabilities and operational efficiency by developing extensive datasets to improve reproducibility and clinical relevance, particularly with Generative Adversarial Networks (GANs) [39]. Early feedback from radiologists ensures clinical alignment, while refining logical neural network (LNN) methods enhances predicate generalization for complex tasks [5]. Efforts to improve collaboration between retrievers and large language models (LLMs) seek to minimize hallucinations and enhance structured outputs [37].

In personalized healthcare, integrating multimodal data and LLMs provides tailored mental health support by focusing on empathetic responses. Models like GatorTron improve performance in complex natural language processing (NLP) tasks [29]. Future research aims to refine cohort definitions, expand computable variables in real-world data, and explore applications in various disease areas, broadening AI's impact in healthcare [41]. Enhancing LLM robustness and efficiency in optimization contexts remains crucial [32].

User-centered approaches are being developed to enhance AI system explainability, fostering trust and adoption in clinical settings [27]. Research on sampling strategies addresses data challenges across domains, enabling AI models to manage diverse datasets effectively [34]. Continuous innovation in AI model capabilities is essential, particularly through healthcare foundation models (HFMs) that bridge traditional AI limitations and diverse healthcare practices. Understanding HFMs' operational mechanisms and challenges remains a priority, alongside effective organizational governance for AI adoption in healthcare, as exemplified by the Health AI Partnership (HAIP) [15, 65].

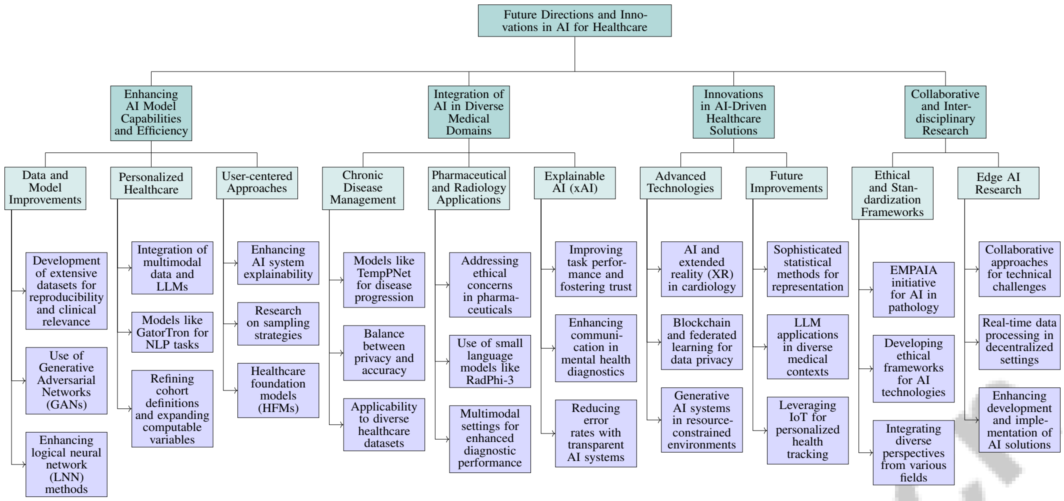

Figure 3: This figure illustrates the future directions and innovations in AI for healthcare, highlighting key areas such as enhancing model capabilities and efficiency, integrating AI across diverse medical domains, innovations in AI-driven healthcare solutions, and the importance of collaborative and interdisciplinary research efforts. Each category is further detailed with specific advancements and research initiatives aimed at improving patient care, operational efficiencies, and ethical standards in the rapidly evolving field of AI in healthcare.

7.2 Integration of AI in Diverse Medical Domains

AI's integration into various medical domains extends beyond anesthesia, enhancing diagnostic accuracy, treatment personalization, and operational efficiencies. In chronic disease management, models like TempPNet track disease progression in conditions such as Parkinson's disease, showcasing AI's adaptability to sensor data and comprehensive chronic care. Future research should optimize the balance between privacy and accuracy in real-world applications while exploring the method's applicability to other healthcare datasets [1].

In respiratory diseases, expanding AI models for detecting additional conditions and enhancing integration with smart devices for continuous monitoring is vital for improving patient outcomes. The application of AI in multilingual medical text generation, demonstrated by the Medical MT5 model, emphasizes the need for diverse datasets and improved evaluation metrics to support linguistic needs in healthcare [35].

The pharmaceutical industry is transforming through AI, with future research addressing ethical concerns, improving data integration, and exploring AI's potential in personalized medicine and patient engagement [57]. The use of small language models like RadPhi-3 in radiology suggests expanding training datasets to include various radiology reports and investigating multimodal settings for enhanced diagnostic performance [4].

Future directions include developing frameworks for ethical AI integration in management and exploring AI's long-term implications on workforce dynamics. The incorporation of explainable AI (xAI) across medical domains is essential for enhancing task performance and fostering trust in AI systems. Recent trends indicate that large language models can improve explainability in mental health diagnostics, addressing the black-box nature of AI algorithms and facilitating collaboration between AI and healthcare professionals [25, 83, 27, 26].

The integration of AI into diverse medical domains underscores its potential to revolutionize healthcare delivery. By addressing challenges related to data diversity, model adaptability, and explainability, AI technologies can significantly enhance patient care and operational efficiencies. Advancements in LLMs can improve communication between cancer patients and providers, addressing barriers such as knowledge gaps and resource limitations. Moreover, explainable AI reduces error rates among healthcare professionals when supported by transparent AI systems, enriching patient-provider interactions and optimizing clinical decision-making processes [25, 2, 10].

7.3 Innovations in AI-Driven Healthcare Solutions

Innovative AI-driven solutions are transforming healthcare delivery through advanced technologies such as AI, extended reality (XR), blockchain, and federated learning. In cardiology, combining AI and XR enhances diagnostic and treatment planning capabilities, leading to improved patient outcomes [11]. These advancements create immersive experiences that aid clinicians in visualizing complex cardiac conditions for more personalized care.

The integration of blockchain and federated learning addresses critical data privacy and security challenges while enabling collaborative research and data sharing across decentralized networks [86]. This ensures secure and efficient data management, allowing healthcare providers to leverage AI-driven insights without compromising patient confidentiality.

Generative AI systems, particularly those employing Retrieval-Augmented Generation (RAG) approaches, are effective in resource-constrained environments, crucial for expanding access to advanced healthcare technologies in underserved areas [37]. Future improvements in AI-driven healthcare solutions may involve developing sophisticated statistical methods for capturing finer-grained representations, enhancing LLM applications across diverse medical contexts [64].

These innovations illustrate the transformative potential of integrating advanced technologies into healthcare delivery, paving the way for more efficient, personalized, and accessible medical care. As these technologies evolve, they promise to enhance patient outcomes and operational efficiencies by improving patient-clinician interactions, leveraging IoT for personalized health tracking, and utilizing foundation models that adapt to diverse healthcare needs. Such advancements facilitate better health data interpretation and enable effective disease management strategies, ultimately leading to informed clinical decisions and improved patient care [44, 65, 72, 24].

7.4 Collaborative and Interdisciplinary Research

The advancement of AI in healthcare is intrinsically linked to collaborative and interdisciplinary research efforts essential for addressing complex challenges and ethical considerations in this rapidly evolving field. The EMPAIA initiative exemplifies the importance of such collaboration by establishing a sustainable infrastructure for AI in pathology through the non-profit EMPAIA International association. This initiative underscores the need for a unified approach to integrating AI technologies into clinical practice, fostering an environment that supports innovation and standardization [14].

Future research must prioritize developing ethical frameworks that can adapt to the dynamic landscape of AI technologies. This involves continuous scrutiny and interdisciplinary collaboration to ensure ethical guidelines remain relevant and effective [67]. Integrating diverse perspectives from medicine, ethics, law, and computer science is crucial for developing comprehensive ethical guidelines that address the multifaceted challenges posed by AI in healthcare [81].

Moreover, the advancement of edge AI research highlights the significance of collaborative, multidisciplinary approaches, essential for overcoming technical and logistical challenges associated with deploying AI technologies in decentralized healthcare settings, where real-time data processing and decision-making are critical [23]. By fostering a collaborative research environment, stakeholders can leverage diverse expertise to enhance the development and implementation of AI solutions that improve patient care and operational efficiencies.

8 Conclusion

The integration of artificial intelligence (AI) into healthcare is reshaping the landscape of medical practice, significantly enhancing diagnostic precision, treatment personalization, and operational efficiency. Generative AI and large language models (LLMs) are pivotal in advancing healthcare by generating synthetic data, refining diagnostics, and tailoring treatments, thereby transforming patient care. In anesthesia, AI's role in monitoring, predicting outcomes, and optimizing delivery is critical for improving patient safety and clinical efficacy. However, challenges such as data privacy, algorithmic bias, and the need for transparency and explainability persist, highlighting the importance of developing robust ethical frameworks and fostering interdisciplinary collaboration for responsible AI deployment. Emphasizing sustainable AI practices, particularly in medical imaging, and advancing causal inference methodologies are crucial for ongoing innovation. Addressing these challenges through collaborative research will enable the healthcare sector to fully harness AI's potential, driving substantial improvements in patient outcomes and healthcare delivery.

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References

[1] Mehdi Letafati and Safa Otoum. Global differential privacy for distributed metaverse healthcare systems, 2023.

[2] Wonyoung So, Edyta P. Bogucka, Sanja Šćepanović, Sagar Joglekar, Ke Zhou, and Daniele Quercia. Humane visual ai: Telling the stories behind a medical condition, 2020.

[3] Mahta Ramezanian Panahi, Germán Abrevaya, Jean-Christophe Gagnon-Audet, Vikram Voleti, Irina Rish, and Guillaume Dumas. Generative models of brain dynamics – a review, 2021.

[4] Kyungsu Kim, Junhyun Park, Saul Langarica, Adham Mahmoud Alkhadrawi, and Synho Do. Integrating chatgpt into secure hospital networks: A case study on improving radiology report analysis, 2024.

[5] Yeldar Toleubay, Don Joven Agravante, Daiki Kimura, Baihan Lin, Djallel Bouneffouf, and Michiaki Tatsubori. Utterance classification with logical neural network: Explainable ai for mental disorder diagnosis, 2023.

[6] Hongyi Yang, Fangyuan Chang, Dian Zhu, Muroi Fumie, and Zhao Liu. Application of artificial intelligence in schizophrenia rehabilitation management: A systematic scoping review, 2025.

[7] Hanyao Huang, Ou Zheng, Dongdong Wang, Jiayi Yin, Zijin Wang, Shengxuan Ding, Heng Yin, Chuan Xu, Renjie Yang, Qian Zheng, and Bing Shi. Chatgpt for shaping the future of dentistry: The potential of multi-modal large language model, 2023.

[8] Huanqian Wang, Yang Yue, Rui Lu, Jingxin Shi, Andrew Zhao, Shenzhi Wang, Shiji Song, and Gao Huang. Model surgery: Modulating llm's behavior via simple parameter editing, 2025.

[9] Poorvesh Dongre, Majid Behravan, Kunal Gupta, Mark Billinghurst, and Denis Gračanin. Integrating physiological data with large language models for empathic human-ai interaction, 2024.

[10] Ziqi Yang, Xuhai Xu, Bingsheng Yao, Jiachen Li, Jennifer Bagdasarian, Guodong Gao, and Dakuo Wang. "i wish there were an ai": Challenges and ai potential in cancer patient-provider communication, 2024.

[11] Zofia Rudnicka, Klaudia Proniewska, Mark Perkins, and Agnieszka Pregowska. Health digital twins supported by artificial intelligence-based algorithms and extended reality in cardiology, 2024.

[12] Raju Vaishya, Mohd Javaid, Ibrahim Haleem Khan, and Abid Haleem. Artificial intelligence (ai) applications for covid-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, 14(4):337–339, 2020.

[13] Rohan Pandey, Vaibhav Gautam, Ridam Pal, Harsh Bandhey, Lovedeep Singh Dhingra, Himanshu Sharma, Chirag Jain, Kanav Bhagat, Arushi, Lajjaben Patel, Mudit Agarwal, Samprati Agrawal, Rishabh Jalan, Akshat Wadhwa, Ayush Garg, Vihaan Misra, Yashwin Agrawal, Bhavika Rana, Ponnurangam Kumaraguru, and Tavpritesh Sethi. A machine learning application for raising wash awareness in the times of covid-19 pandemic, 2020.

[14] Norman Zerbe, Lars Ole Schwen, Christian Geißler, Katja Wiesemann, Tom Bisson, Peter Boor, Rita Carvalho, Michael Franz, Christoph Jansen, Tim-Rasmus Kiehl, Björn Lindequist, Nora Charlotte Pohlan, Sarah Schmell, Klaus Strohmenger, Falk Zakrzewski, Markus Plass, Michael Takla, Tobias Küster, André Homeyer, and Peter Hufnagl. Joining forces for pathology diagnostics with ai assistance: The empaia initiative, 2024.

[15] Jee Young Kim, William Boag, Freya Gulamali, Alifia Hasan, Henry David Jeffry Hogg, Mark Lifson, Deirdre Mulligan, Manesh Patel, Inioluwa Deborah Raji, Ajai Sehgal, Keo Shaw, Danny Tobey, Alexandra Valladares, David Vidal, Suresh Balu, and Mark Sendak. Organizational governance of emerging technologies: Ai adoption in healthcare, 2023.

[16] Randal S. Olson, Moshe Sipper, William La Cava, Sharon Tartarone, Steven Vitale, Weixuan Fu, Patryk Orzechowski, Ryan J. Urbanowicz, John H. Holmes, and Jason H. Moore. A system for accessible artificial intelligence, 2017.

[17] Meredith Ringel Morris, Carrie J. Cai, Jess Holbrook, Chinmay Kulkarni, and Michael Terry. The design space of generative models, 2023.

[18] Suyi Zhang, Ekram Alam, Jack Baber, Francesca Bianco, Edward Turner, Maysam Chamanzar, and Hamid Dehghani. Mindspeech: Continuous imagined speech decoding using high-density fnirs and prompt tuning for advanced human-ai interaction, 2024.

[19] Zilong Wang, Nan Chen, Luna K. Qiu, Ling Yue, Geli Guo, Yang Ou, Shiqi Jiang, Yuqing Yang, and Lili Qiu. The potential and value of ai chatbot in personalized cognitive training, 2024.

[20] Toshiaki Koike-Akino and Ye Wang. queegnet: Quantum ai for biosignal processing, 2022.

[21] Gaurav Singh and Kavitesh Kumar Bali. Enhancing decision-making in optimization through llm-assisted inference: A neural networks perspective, 2024.

[22] Dario Gil, Stacy Hobson, Aleksandra Mojsilović, Ruchir Puri, and John R Smith. Ai for management: An overview. *The future of management in an AI world: Redefining purpose and strategy in the fourth industrial revolution*, pages 3–19, 2019.

[23] Elisa Bertino and Sujata Banerjee. Artificial intelligence at the edge, 2020.

[24] Oded Nov, Yindalon Aphinyanaphongs, Yvonne W. Lui, Devin Mann, Maurizio Porfiri, Mark Riedl, John-Ross Rizzo, and Batia Wiesenfeld. The transformation of patient-clinician relationships with ai-based medical advice: A "bring your own algorithm" era in healthcare, 2020.

[25] Julian Senoner, Simon Schallmoser, Bernhard Kratzwald, Stefan Feuerriegel, and Torbjørn Netland. Explainable ai improves task performance in human-ai collaboration, 2024.

[26] Adam Perrett. Emergent explainability: Adding a causal chain to neural network inference, 2024.

[27] Katharina Weitz, Alexander Zellner, and Elisabeth André. What do end-users really want? investigation of human-centered xai for mobile health apps, 2022.

[28] Mingyu Derek Ma, Chenchen Ye, Yu Yan, Xiaoxuan Wang, Peipei Ping, Timothy S Chang, and Wei Wang. Clibench: A multifaceted and multigranular evaluation of large language models for clinical decision making, 2024.

[29] Xi Yang, Aokun Chen, Nima PourNejatian, Hoo Chang Shin, Kaleb E Smith, Christopher Parisien, Colin Compas, Cheryl Martin, Mona G Flores, Ying Zhang, Tanja Magoc, Christopher A Harle, Gloria Lipori, Duane A Mitchell, William R Hogan, Elizabeth A Shenkman, Jiang Bian, and Yonghui Wu. Gatortron: A large clinical language model to unlock patient information from unstructured electronic health records, 2022.

[30] Liam Hazan, Gili Focht, Naama Gavrielov, Roi Reichart, Talar Hagopian, Mary-Louise C. Greer, Ruth Cytter Kuint, Dan Turner, and Moti Freiman. Leveraging prompt-learning for structured information extraction from crohn's disease radiology reports in a low-resource language, 2024.

[31] Iker García-Ferrero, Rodrigo Agerri, Aitziber Atutxa Salazar, Elena Cabrio, Iker de la Iglesia, Alberto Lavelli, Bernardo Magnini, Benjamin Molinet, Johana Ramirez-Romero, German Rigau, Jose Maria Villa-Gonzalez, Serena Villata, and Andrea Zaninello. Medical mt5: An open-source multilingual text-to-text llm for the medical domain, 2024.

[32] Sen Huang, Kaixiang Yang, Sheng Qi, and Rui Wang. When large language model meets optimization, 2024.

[33] Zongyuan Ge and Xin Wang. Evaluation of various open-set medical imaging tasks with deep neural networks, 2021.

[34] Tingyi Wanyan, Jing Zhang, Ying Ding, Ariful Azad, Zhangyang Wang, and Benjamin S Glicksberg. Bootstrapping your own positive sample: Contrastive learning with electronic health record data, 2021.

[35] Shannon L. Walston, Hiroshi Seki, Hirotaka Takita, Yasuhito Mitsuyama, Shingo Sato, Akifumi Hagiwara, Rintaro Ito, Shouhei Hanaoka, Yukio Miki, and Daiju Ueda. Data set terminology of deep learning in medicine: A historical review and recommendation, 2024.

[36] Mohammad Shahab Sepehri, Zalan Fabian, Maryam Soltanolkotabi, and Mahdi Soltanolkotabi. Mediconfusion: Can you trust your ai radiologist? probing the reliability of multimodal medical foundation models, 2024.

[37] Patrice Béchard and Orlando Marquez Ayala. Reducing hallucination in structured outputs via retrieval-augmented generation, 2024.

[38] Weiwen Wu, Chuang Niu, Shadi Ebrahimian, Hengyong Yu, Mannu Kalra, and Ge Wang. Ai-enabled ultra-low-dose ct reconstruction, 2021.

[39] Hazrat Ali, Christer Gronlund, and Zubair Shah. Leveraging gans for data scarcity of covid-19: Beyond the hype, 2023.

[40] Ali Imran, Iryna Posokhova, Haneya N. Qureshi, Usama Masood, Muhammad Sajid Riaz, Kamran Ali, Charles N. John, MD Iftikhar Hussain, and Muhammad Nabeel. Ai4covid-19: Ai enabled preliminary diagnosis for covid-19 from cough samples via an app, 2020.

[41] Xiong Liu, Cheng Shi, Uday Deore, Yingbo Wang, Myah Tran, Iya Khalil, and Murthy Devarakonda. A scalable ai approach for clinical trial cohort optimization, 2021.

[42] Francisco Castro, Jian Gao, and Sébastien Martin. Human-ai interactions and societal pitfalls, 2023.

[43] Xiang Li, Shunpan Liang, Yulei Hou, and Tengfei Ma. Stratmed: Relevance stratification between biomedical entities for sparsity on medication recommendation, 2023.

[44] Pengcheng Chen, Ziyan Huang, Zhongying Deng, Tianbin Li, Yanzhou Su, Haoyu Wang, Jin Ye, Yu Qiao, and Junjun He. Enhancing medical task performance in gpt-4v: A comprehensive study on prompt engineering strategies, 2023.

[45] Noel C. F. Codella, Ying Jin, Shrey Jain, Yu Gu, Ho Hin Lee, Asma Ben Abacha, Alberto Santamaria-Pang, Will Guyman, Naiteek Sangani, Sheng Zhang, Hoifung Poon, Stephanie Hyland, Shruthi Bannur, Javier Alvarez-Valle, Xue Li, John Garrett, Alan McMillan, Gaurav Rajguru, Madhu Maddi, Nilesh Vijayrania, Rehaan Bhimai, Nick Mecklenburg, Rupal Jain, Daniel Holstein, Naveen Gaur, Vijay Aski, Jenq-Neng Hwang, Thomas Lin, Ivan Tarapov, Matthew Lungren, and Mu Wei. Medimageinsight: An open-source embedding model for general domain medical imaging, 2024.

[46] Yu Han and Jingwen Tao. Revolutionizing pharma: Unveiling the ai and llm trends in the pharmaceutical industry, 2024.

[47] Ramesh Raskar, Praneeth Vepakomma, Tristan Swedish, and Aalekh Sharan. Data markets to support ai for all: Pricing, valuation and governance, 2019.

[48] Mercy Ranjit, Shaury Srivastav, and Tanuja Ganu. Radphi-3: Small language models for radiology, 2024.

[49] Liyan Tang, Yifan Peng, Yanshan Wang, Ying Ding, Greg Durrett, and Justin F. Rousseau. Less likely brainstorming: Using language models to generate alternative hypotheses, 2023.

[50] Antonios Alexos, Yu-Dai Tsai, Ian Domingo, Maryam Pishgar, and Pierre Baldi. Neural erosion: Emulating controlled neurodegeneration and aging in ai systems, 2024.

[51] Kathryn Schutte, Olivier Moindrot, Paul Hérent, Jean-Baptiste Schiratti, and Simon Jégou. Using stylegan for visual interpretability of deep learning models on medical images, 2021.

[52] Sabrina Toro, Anna V Anagnostopoulos, Sue Bello, Kai Blumberg, Rhiannon Cameron, Leigh Carmody, Alexander D Diehl, Damion Dooley, William Duncan, Petra Fey, Pascale Gaudet, Nomi L Harris, Marcin Joachimiak, Leila Kiani, Tiago Lubiana, Monica C Munoz-Torres, Shawn O'Neil, David Osumi-Sutherland, Aleix Puig, Justin P Reese, Leonore Reiser, Sofia

Robb, Troy Ruemping, James Seager, Eric Sid, Ray Stefancsik, Magalie Weber, Valerie Wood, Melissa A Haendel, and Christopher J Mungall. Dynamic retrieval augmented generation of ontologies using artificial intelligence (dragon-ai), 2024.

[53] Donghoon Shin, Gary Hsieh, and Young-Ho Kim. Planfitting: Tailoring personalized exercise plans with large language models, 2023.

[54] Marta Buetas Arcas, Richard Osuala, Karim Lekadir, and Oliver Díaz. Mitigating annotation shift in cancer classification using single image generative models, 2024.

[55] Nadezhda Koriakina, Nataša Sladoje, Vladimir Bašić, and Joakim Lindblad. Oral cancer detection and interpretation: Deep multiple instance learning versus conventional deep single instance learning, 2022.

[56] Siyuan Yan, Zhen Yu, Clare Primiero, Cristina Vico-Alonso, Zhonghua Wang, Litao Yang, Philipp Tschandl, Ming Hu, Gin Tan, Vincent Tang, Aik Beng Ng, David Powell, Paul Bonnington, Simon See, Monika Janda, Victoria Mar, Harald Kittler, H. Peter Soyer, and Zongyuan Ge. A general-purpose multimodal foundation model for dermatology, 2024.

[57] Zainab Iftikhar, Sean Ransom, Amy Xiao, and Jeff Huang. Therapy as an nlp task: Psychologists' comparison of llms and human peers in cbt, 2024.

[58] Aryan Jadon and Shashank Kumar. Leveraging generative ai models for synthetic data generation in healthcare: Balancing research and privacy, 2023.

[59] Frank Joublin, Antonello Ceravola, Joerg Deigmoeller, Michael Gienger, Mathias Franzius, and Julian Eggert. A glimpse in chatgpt capabilities and its impact for ai research, 2023.

[60] Bhashithe Abeysinghe and Ruhan Circi. The challenges of evaluating llm applications: An analysis of automated, human, and llm-based approaches, 2024.

[61] Q. Vera Liao and Jennifer Wortman Vaughan. Ai transparency in the age of llms: A human-centered research roadmap, 2023.

[62] Fujian Jia, Xin Liu, Lixi Deng, Jiwen Gu, Chunchao Pu, Tunan Bai, Mengjiang Huang, Yuanzhi Lu, and Kang Liu. Oncogpt: A medical conversational model tailored with oncology domain expertise on a large language model meta-ai (llama), 2024.

[63] Ehud Karpas, Omri Abend, Yonatan Belinkov, Barak Lenz, Opher Lieber, Nir Ratner, Yoav Shoham, Hofit Bata, Yoav Levine, Kevin Leyton-Brown, Dor Muhlgay, Noam Rozen, Erez Schwartz, Gal Shachaf, Shai Shalev-Shwartz, Amnon Shashua, and Moshe Tenenholtz. Mrkl systems: A modular, neuro-symbolic architecture that combines large language models, external knowledge sources and discrete reasoning, 2022.

[64] Randall Balestriero, Romain Cosentino, and Sarath Shekkizhar. Characterizing large language model geometry helps solve toxicity detection and generation, 2024.

[65] Yuting He, Fuxiang Huang, Xinrui Jiang, Yuxiang Nie, Minghao Wang, Jiguang Wang, and Hao Chen. Foundation model for advancing healthcare: Challenges, opportunities, and future directions, 2024.

[66] S. M Towhidul Islam Tonmoy, S M Mehedi Zaman, Vinija Jain, Anku Rani, Vipula Rawte, Aman Chadha, and Amitava Das. A comprehensive survey of hallucination mitigation techniques in large language models, 2024.

[67] Junfeng Jiao, Saleh Afroogh, Yiming Xu, and Connor Phillips. Navigating llm ethics: Advancements, challenges, and future directions, 2024.

[68] Hang Dong, Matúš Falis, William Whiteley, Beatrice Alex, Joshua Matterson, Shaoxiong Ji, Jiaoyan Chen, and Honghan Wu. Automated clinical coding: What, why, and where we are?, 2022.

[69] Chanseo Lee, Sonu Kumar, Kimon A. Vogt, Sam Meraj, and Antonia Vogt. Advancing complex medical communication in arabic with sporo arasum: Surpassing existing large language models, 2024.

[70] Xiangyu Peng, Kai Wang, Jianfei Yang, Yingying Zhu, and Yang You. More than positive and negative: Communicating fine granularity in medical diagnosis, 2024.

[71] Jiaheng Xie, Xiaohang Zhao, Xiang Liu, and Xiao Fang. Care for the mind amid chronic diseases: An interpretable ai approach using iot, 2022.

[72] Amit Sheth, Utkarshani Jaimini, and Hong Yung Yip. How will the internet of things enable augmented personalized health?, 2017.

[73] Emmett D. Goodman, Krishna K. Patel, Yilun Zhang, William Locke, Chris J. Kennedy, Rohan Mehrotra, Stephen Ren, Melody Y. Guan, Maren Downing, Hao Wei Chen, Jevin Z. Clark, Gabriel A. Brat, and Serena Yeung. A real-time spatiotemporal ai model analyzes skill in open surgical videos, 2021.

[74] Xiaochen Wang, Jiaqi Wang, Houping Xiao, Jinghui Chen, and Fenglong Ma. Fedkim: Adaptive federated knowledge injection into medical foundation models, 2024.

[75] Szymon Mazurek, Monika Pytlarz, Sylwia Malec, and Alessandro Crimi. Investigation of energy-efficient ai model architectures and compression techniques for "green" fetal brain segmentation, 2024.

[76] Soroosh Tayebi Arasteh, Peter Isfort, Marwin Saehn, Gustav Mueller-Franzes, Firas Khader, Jakob Nikolas Kather, Christiane Kuhl, Sven Nebelung, and Daniel Truhn. Collaborative training of medical artificial intelligence models with non-uniform labels, 2023.

[77] Yuanyuan Wei, Xianxian Liu, Changran Xu, Guoxun Zhang, Wu Yuan, Ho-Pui Ho, and Mingkun Xu. Artificial intelligence enhanced digital nucleic acid amplification testing for precision medicine and molecular diagnostics, 2024.

[78] Fadhil G. Al-Amran, Abbas M. Hezam, Salman Rawaf, and Maitham G. Yousif. Genomic analysis and artificial intelligence: Predicting viral mutations and future pandemics, 2023.

[79] S. Kevin Zhou, Hayit Greenspan, Christos Davatzikos, James S. Duncan, Bram van Ginneken, Anant Madabhushi, Jerry L. Prince, Daniel Rueckert, and Ronald M. Summers. A review of deep learning in medical imaging: Imaging traits, technology trends, case studies with progress highlights, and future promises, 2021.

[80] Neel Kanwal, Emiel A. M. Janssen, and Kjersti Engan. Balancing privacy and progress in artificial intelligence: Anonymization in histopathology for biomedical research and education, 2023.

[81] Niina Zuber, Severin Kacianka, and Jan Gogoll. Big data ethics, machine ethics or information ethics? navigating the maze of applied ethics in it, 2022.

[82] Reihaneh Torkzadehmahani, Reza Nasirigerdeh, David B. Blumenthal, Tim Kacprowski, Markus List, Julian Matschinske, Julian Späth, Nina Kerstin Wenke, Béla Bihari, Tobias Frisch, Anne Hartebrodt, Anne-Christin Hausschild, Dominik Heider, Andreas Holzinger, Walter Hötzendorfer, Markus Kastelitz, Rudolf Mayer, Cristian Nogales, Anastasia Pustozerova, Richard Röttger, Harald H. H. W. Schmidt, Ameli Schwalber, Christof Tschohl, Andrea Wohner, and Jan Baumbach. Privacy-preserving artificial intelligence techniques in biomedicine, 2020.

[83] Yusif Ibrahimov, Tarique Anwar, and Tommy Yuan. Explainable ai for mental disorder detection via social media: A survey and outlook, 2024.

[84] HLEG AI. High-level expert group on artificial intelligence. *Ethics guidelines for trustworthy AI*, 6, 2019.

[85] Romain-Daniel Gosselin. Ai detectors are poor western blot classifiers: A study of accuracy and predictive values, 2024.

[86] Abdulrezzak Zekiye and Öznur Özkasap. Decentralized healthcare systems with federated learning and blockchain, 2023.

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