Telemedicine and AI in Healthcare: A Survey

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Abstract

This survey paper provides a comprehensive exploration of the integration of telemedicine and artificial intelligence (AI) in healthcare, emphasizing the transformative impact of these technologies on patient care and outcomes. Key areas of focus include telemedicine's role in crisis management, AI-driven diagnostics and treatment planning, the development and application of medical large language models (LLMs) and vision-language models, and the digital transformation of healthcare practices. The survey highlights the significant advancements in remote patient monitoring, AI's role in enhancing clinical decision-making, and the integration of machine learning with electronic health records (EHRs). Challenges such as data privacy, ethical considerations, and the interpretability of AI models are discussed, alongside potential solutions and future research directions. The paper underscores the importance of innovative healthcare delivery models and AI solutions in improving patient outcomes, particularly in cancer care. By examining the multifaceted impact of healthcare innovations, the survey provides insights into the ongoing digital health transformation and its implications for enhancing diagnostic accuracy, treatment efficiency, and overall healthcare delivery. The findings emphasize the need for continued research and development to address existing challenges and maximize the potential benefits of telemedicine and AI technologies in healthcare.

1 Introduction

1.1 Structure of the Survey

This survey provides a comprehensive examination of the integration of telemedicine and artificial intelligence (AI) in healthcare, focusing on how AI enhances diagnostic accuracy, treatment personalization, and patient outcomes while addressing ethical challenges and biases. It analyzes the strengths and weaknesses of AI applications, such as Google's Gemini as a virtual doctor, and emphasizes the importance of diverse datasets and fairness-aware algorithms, offering insights for future research and responsible AI application in clinical settings [1, 2, 3, 4, 5].

The paper begins with an introduction that contextualizes the pivotal role of advanced technologies in improving patient care. Section 2 provides background and definitions, detailing core concepts such as telemedicine, AI in healthcare, pandemic healthcare, medical large language models (LLMs), vision-language models, digital health transformation, remote patient monitoring, and healthcare innovation.

Section 3 focuses on telemedicine and remote patient monitoring, particularly their significance during crises like pandemics, with a subsection examining their effectiveness in crisis management. Section 4 shifts to AI in healthcare, discussing its applications in diagnostics and treatment planning, alongside its impact on patient outcomes. This section also addresses challenges in AI implementation, ethical considerations, and innovative techniques for enhancing AI performance in healthcare.

Section 5 explores the development and application of medical LLMs and vision-language models, underscoring their role in providing medical insights and improving clinical decision-making. Section

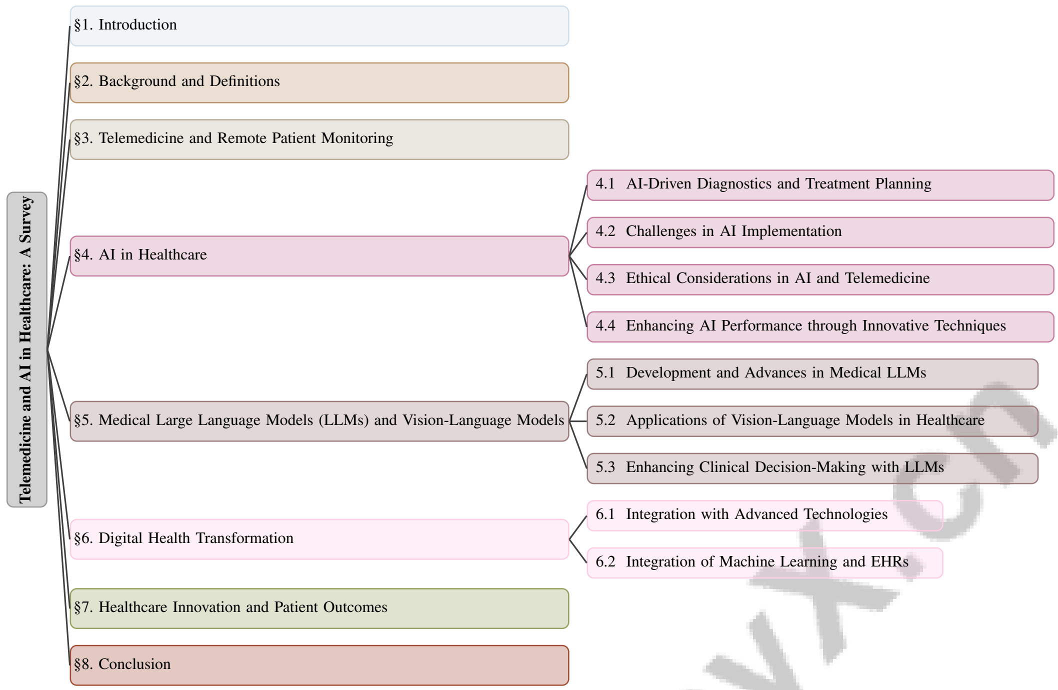

Figure 1: chapter structure

6 analyzes how traditional healthcare practices are transformed by digital health solutions, particularly through mobile health applications, telemedicine, and AI. It highlights the role of machine learning in enhancing electronic health records (EHRs) by improving data accuracy, enabling predictive modeling for patient outcomes, and facilitating personalized care, while addressing challenges related to data privacy, interoperability, and algorithmic bias [6, 1, 7, 8, 9].

Section 7 discusses healthcare innovation and its influence on patient outcomes, emphasizing the role of advanced technologies in healthcare delivery and patient satisfaction. This section also addresses AI solutions in cancer care and innovative healthcare delivery models. The survey concludes with Section 8, summarizing key points and reflecting on future directions for telemedicine and AI in healthcare, along with challenges and potential research opportunities.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Background and Definitions

Advanced technologies have revolutionized healthcare delivery, enhancing accessibility and efficiency. Telemedicine, a pivotal component of this transformation, facilitates remote consultations and monitoring, crucially extending healthcare to underserved regions and during global crises [10]. This modality is instrumental in improving healthcare quality in resource-limited settings by enabling continuous care without the need for extensive physical infrastructure. Sustainable business models and e-health initiatives further enhance telemedicine's scalability and viability [11].

Artificial Intelligence (AI) introduces a paradigm shift in healthcare through its capabilities in diagnostics, treatment planning, and personalized care, particularly in precision medicine [3]. However, AI's integration raises significant concerns about bias, fairness, and ethical issues, especially in diverse environments. The opacity of AI clinical decision support systems (CDSS) can engender mistrust among clinicians, hindering AI adoption in healthcare [12]. Moreover, the reliance on self-reported data in automatic disease diagnosis systems underscores the need for precise data collection to avoid inaccuracies [13].

Medical Large Language Models (LLMs) and vision-language models are transforming healthcare by synthesizing insights from extensive datasets, such as Electronic Health Records (EHRs) and medical imaging, thereby enhancing clinical decision-making accuracy [14]. The application of interpretable machine learning (IML) and explainable artificial intelligence (XAI) is essential for building transparency and trust in AI-driven healthcare solutions [13].

Digital health transformation involves integrating cyber-physical systems and advanced networks like 5G to address data fragmentation and manual inefficiencies [11]. The Internet of Medical Things (IoMT) exemplifies this transformation, offering new pathways for healthcare innovation through its applications and enabling technologies [15]. Remote patient monitoring, a core aspect of telemedicine, leverages these technologies to continuously track health metrics, enabling timely interventions and improved outcomes [11].

Machine learning techniques in healthcare innovation aim to improve patient outcomes and operational efficiencies. Despite these advancements, disparities in healthcare access, particularly among marginalized populations, remain significant challenges, often exacerbated by socioeconomic factors [16]. The convergence of telemedicine, AI, and digital health technologies marks a significant advancement in healthcare innovation, offering new opportunities for enhancing patient care and addressing the complexities of modern medical practice [17]. Responsible AI practices that mitigate data uncertainty and health information disorder are crucial for the sustainable integration of AI into healthcare. Explainable AI (XAI) plays a vital role in improving the interpretability of AI models, ensuring patient safety and fostering trust in AI-driven healthcare solutions [13].

The integration of telemedicine into healthcare systems has been significantly influenced by various factors, including crisis management and technological advancements. As illustrated in Figure 2, the hierarchical structure of telemedicine and remote patient monitoring is depicted, emphasizing its critical role in these areas. This figure not only highlights the application of artificial intelligence and machine learning within telemedicine but also underscores the challenges faced during its implementation. By examining this structure, we can better understand the complexities and interdependencies that characterize modern healthcare delivery systems.

3 Telemedicine and Remote Patient Monitoring

3.1 Telemedicine in Crisis Management

Telemedicine has proven indispensable in maintaining healthcare delivery during crises, as evidenced by its pivotal role during the COVID-19 pandemic. It effectively ensured continuity of care by facilitating remote consultations and minimizing infection risks amid restrictions on in-person visits [18, 19]. The integration of advanced technologies has further enhanced telemedicine's efficacy. For example, the TeleHealthChain protocol utilizes blockchain to secure patient data, addressing critical security concerns during emergencies [20]. Autonomous mobile clinics (AMCs) extend telemedicine's reach by delivering healthcare directly to patients in crisis-affected areas, thus overcoming access and efficiency barriers [21].

In emergency departments, AI-driven solutions optimize patient triage, enabling effective prioritization of care [22]. Deep learning models predict critical outcomes like ICU admissions and mortality, supporting informed decision-making and resource allocation during pandemics [23]. During COVID-19, robust AI models were deployed to address data shifts and enhance patient care [24].

Interactive machine learning systems, such as CoachMe, have increased user engagement and adherence to personalized health interventions [25]. Grid-enabled telemedicine frameworks ensure reliable service delivery in low-resource settings, compensating for inadequate traditional healthcare infrastructure [26]. Platforms like Windows Azure demonstrate the scalability and performance of telemedicine applications under varying loads, highlighting system robustness during healthcare crises [27]. The TeleOR system enhances tele-intervention capabilities in operating rooms, providing real-time surgical guidance even in bandwidth-constrained environments [28].

This is illustrated in Figure 3, which highlights the key components of telemedicine in crisis management, including remote consultations, advanced technologies, and the challenges related to infrastructure and limitations. Despite these advancements, limitations such as the submission of low-quality dermatological images in teledermatology hinder accurate clinical diagnosis [29]. Addressing these issues is essential for enhancing telemedicine's effectiveness in future crises. Additionally, the integration of data work in remote patient monitoring (RPM) affects nurses' workflows and

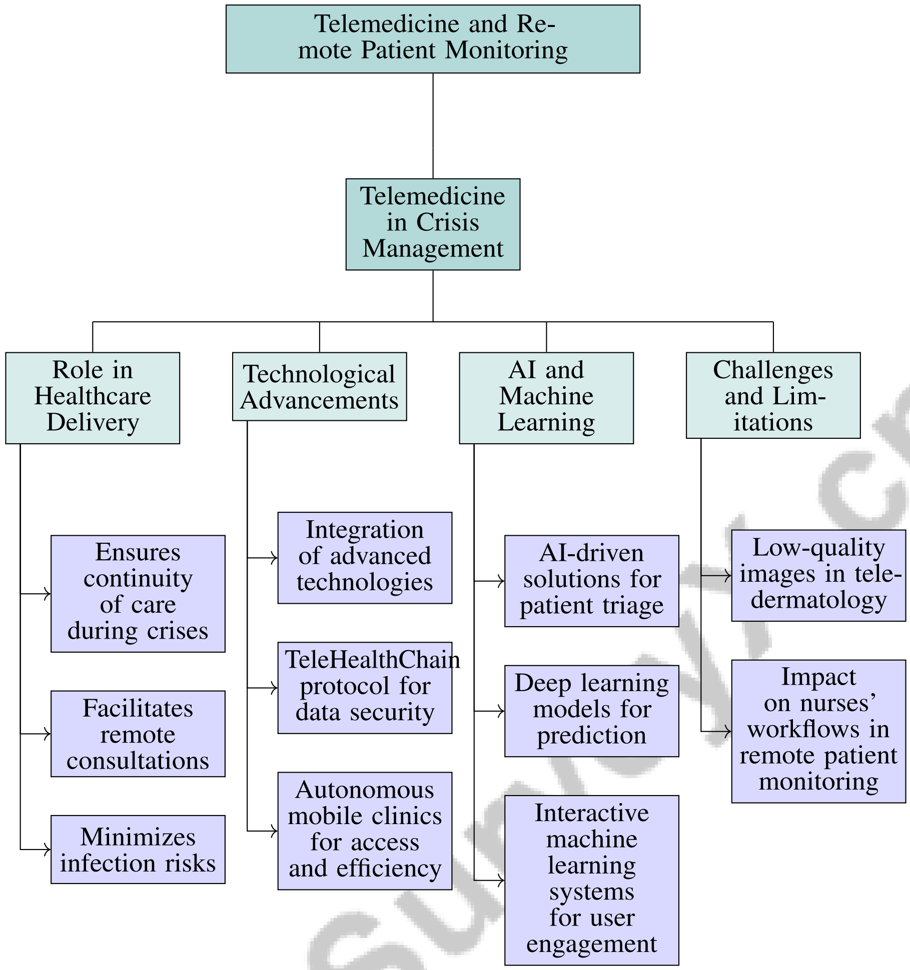

Figure 2: This figure illustrates the hierarchical structure of telemedicine and remote patient monitoring, highlighting its role in crisis management, technological advancements, the application of AI and machine learning, and the challenges faced in implementation.

collaboration strategies, suggesting a need for further exploration to optimize healthcare delivery during emergencies [30]. These technological advancements not only improve crisis management but also lay the groundwork for more resilient healthcare systems.

4 AI in Healthcare

Category	Feature	Method
AI-Driven Diagnostics and Treatment Planning	Domain-Specific Tuning Data Fusion Techniques	AGM-10B[31] MLM-CXR[32]
Ethical Considerations in AI and Telemedicine	Ethical AI Practices	HAS[14], CAPA[33]

Table 1: This table provides a comprehensive overview of the methods employed in AI-driven diagnostics, treatment planning, and ethical considerations in AI and telemedicine. It categorizes the features and specific methodologies applied within these domains, highlighting the integration of domain-specific tuning and data fusion techniques in diagnostics, as well as ethical AI practices in telemedicine. The table serves as a concise reference for understanding the diverse approaches utilized in enhancing healthcare through AI.

The integration of artificial intelligence (AI) into healthcare is reshaping medical practice and patient care, particularly in diagnostics and treatment planning, enhancing clinical decision-making and patient outcomes. Table 2 presents a detailed summary of the methods used in AI-driven diagnostics,

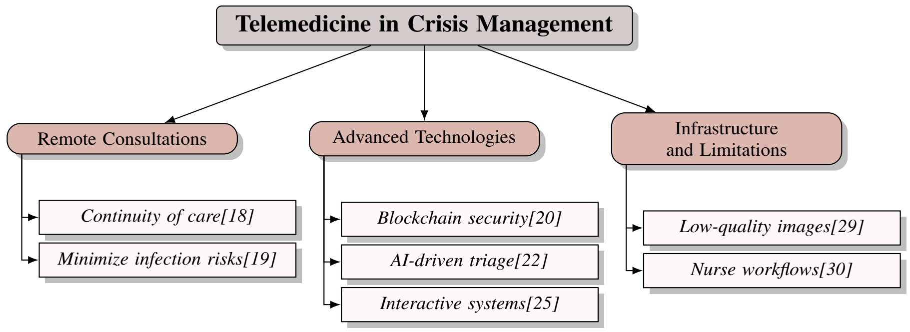

Figure 3: This figure illustrates the key components of telemedicine in crisis management, highlighting remote consultations, advanced technologies, and the challenges related to infrastructure and limitations.

treatment planning, and ethical considerations in AI and telemedicine, illustrating the advancements and challenges within these critical areas of healthcare.

4.1 AI-Driven Diagnostics and Treatment Planning

AI technologies have significantly improved precision and efficiency in medical decision-making by analyzing complex datasets to enhance diagnostic accuracy and treatment outcomes. Fine-tuning pre-trained large language models (LLMs) through optimization processes demonstrates AI's potential to improve medical task performance, providing reliable patient assessments [31]. AI models excel in predicting adverse drug reactions (ADRs), surpassing traditional methods and enabling early intervention. The VisionQaries benchmark illustrates AI's capacity to enhance diagnostic capabilities in visually driven specialties by generating accurate textual responses to clinical queries [12]. Integrating diverse patient data into embeddings for multimodal language models further improves automated chest X-ray (CXR) report generation accuracy [32].

As depicted in Figure 4, the hierarchical structure of AI-driven diagnostics and treatment planning highlights key areas such as AI applications in diagnostics, treatment planning, and ethical considerations in healthcare. AI frameworks that integrate patient-doctor interactions and utilize knowledge graphs for disease classification exemplify its transformative potential in treatment planning. This dual-channel approach leverages deep learning and generative AI to create personalized treatment strategies, enhancing clinical documentation and predictive accuracy for outcomes like 30-day readmission rates [34, 35, 36, 16]. Systems like the Telemedicine Chatbot System (TCS) offer personalized health support through conversational interactions, facilitating healthcare access.

Innovative platforms such as the Dora AI telemedicine system have been rigorously evaluated, revealing both positive ethical implications and potential risks, particularly concerning clinician autonomy. Addressing ethical disparities among stakeholders is crucial for developing safe and ethically sound AI systems [10, 3, 37]. The integration of visual components with AI architectures enhances healthcare dialogue summarization, improving diagnostic and treatment planning.

In medical imaging, AI platforms expedite the deployment of large vision language models (LVLMs) to optimize radiologists' workflows, addressing increasing demands. AI enhances medical imaging processes, improving diagnostic accuracy and patient care. Machine learning and deep learning architectures analyze volumetric data from electronic health records, enhancing prognostic predictions, particularly in head and neck cancers where advanced models excel in tumor segmentation and patient outcome prediction [38, 39, 6, 40].

These advancements in AI-driven diagnostics and treatment planning offer promising avenues for improving healthcare delivery and patient outcomes. AI frameworks simulating sequential decision paths for optimal treatment actions based on evolving patient data highlight AI's transformative potential in ensuring timely and precise medical interventions [24].

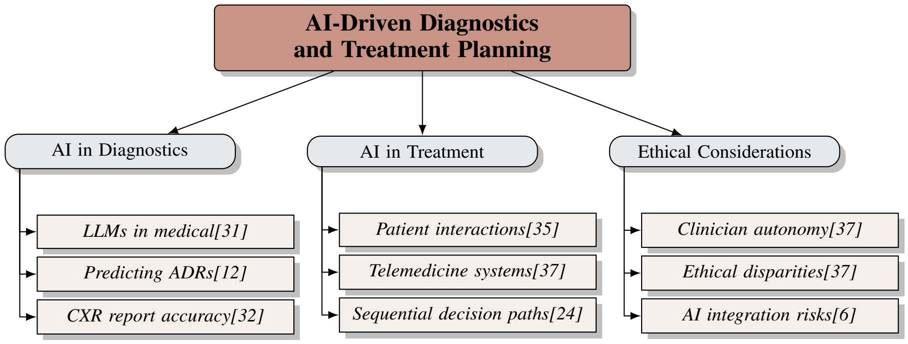

Figure 4: This figure illustrates the hierarchical structure of AI-driven diagnostics and treatment planning, highlighting key areas such as AI applications in diagnostics, treatment planning, and ethical considerations in healthcare.

4.2 Challenges in AI Implementation

The adoption of AI in healthcare faces challenges, notably the black-box nature of advanced models, complicating interpretability for users and developers [41]. This lack of transparency undermines trust among healthcare professionals, essential for AI system integration in clinical settings [24]. The complexity of models often results in high false alarm rates, hindering acceptance in critical decision-making environments [24].

Insufficient specialized training of general LLMs limits their clinical knowledge acquisition, impacting tasks requiring nuanced understanding, such as traditional Chinese medicine (TCM) [31, 42]. Data quality and privacy concerns also pose substantial barriers. Ensuring sufficient data access without compromising patient privacy or violating regulations like HIPAA and GDPR is critical [13]. The integration of diverse data sources requires continuous monitoring and transparency in AI predictions, yet existing methods often fall short [12].

Ethical concerns, patient privacy, and data security remain paramount challenges. The lack of human empathy in AI interactions can adversely affect patient trust and satisfaction [3]. Significant gaps persist in regulatory compliance and understanding clinical validation processes for AI healthcare products, complicating the pathway from development to deployment [43]. Additionally, biases in training data and AI-generated outputs present challenges that must be addressed to establish accountability for AI errors [44]. The integration of AI into healthcare settings is complicated by the friction created by existing technologies, disrupting workflows and increasing cognitive load during data sensemaking [30].

Addressing these challenges requires ongoing research and development to enhance model transparency, data quality, and adaptability across diverse healthcare environments. By tackling key challenges in precision medicine, data integrity, and algorithm development, and leveraging advanced techniques like Natural Language Processing and deep learning, AI can be more effectively integrated into healthcare systems. This integration enhances the accuracy of patient sentiment analysis and personalized therapy plans, facilitating early identification of mental health disorders and ultimately improving patient outcomes and operational efficiencies while fostering a more compassionate, patient-centered approach to care [45, 6].

4.3 Ethical Considerations in AI and Telemedicine

The integration of AI and telemedicine into healthcare systems presents ethical challenges requiring careful examination and regulation. One primary concern is biases within AI models, leading to inequitable healthcare delivery. The underrepresentation of diverse groups in LLM development often results in healthcare outcome disparities, emphasizing the need for diverse data representation in AI training datasets [44]. Cognitive biases in clinical decision-making contribute to diagnostic errors and suboptimal outcomes, necessitating AI systems to effectively address these biases [41].

Clinicians often express hesitancy in trusting AI for decision support due to ethical concerns, including algorithmic opacity and biases [12]. The lack of transparency in AI algorithms, combined with inconsistent data and absent regulatory frameworks, exacerbates these challenges [41]. Frameworks like the GREAT PLEA ethical principles guide the ethical use of Generative AI in healthcare, ensuring safety and ethical acceptability [46].

Data privacy and security remain critical ethical concerns in AI and telemedicine. Ensuring data privacy is paramount, particularly in AI-driven healthcare interventions [33]. Developing datasets prioritizing privacy and security while ensuring ethical compliance is essential for maintaining patient trust [14]. Maintaining patient confidentiality throughout documentation is crucial when deploying AI technologies [44].

The ethical integration of AI and telemedicine faces challenges related to high costs, lack of infrastructure, and the risk of exacerbating existing health and socio-economic disparities [7]. Ensuring fairness, accountability, privacy, robustness, and alignment of Med-LLMs with human values and preferences is essential to address these challenges [44].

Addressing security and privacy concerns is crucial for enhancing technology adoption [10]. The ethical integration of AI and telemedicine necessitates a balanced approach considering personalized feedback, real-time adaptation to patient data, and improved adherence to lifestyle recommendations. These efforts are vital for fostering trust and ensuring technological advancements positively impact healthcare delivery and patient outcomes. The FUTURE-AI framework, focusing on clinical, technical, ethical, and legal risks, provides a structured approach to understanding and mitigating these ethical challenges [47]. Categorizing AI risks into clinical data, technical, and socio-ethical risks offers a comprehensive framework for understanding AI implementation complexities [4].

As illustrated in Figure 5, the key ethical considerations in AI and telemedicine encompass issues related to biases, transparency, data privacy and security, and integration challenges. This figure emphasizes the importance of addressing these concerns to ensure equitable and effective healthcare delivery.

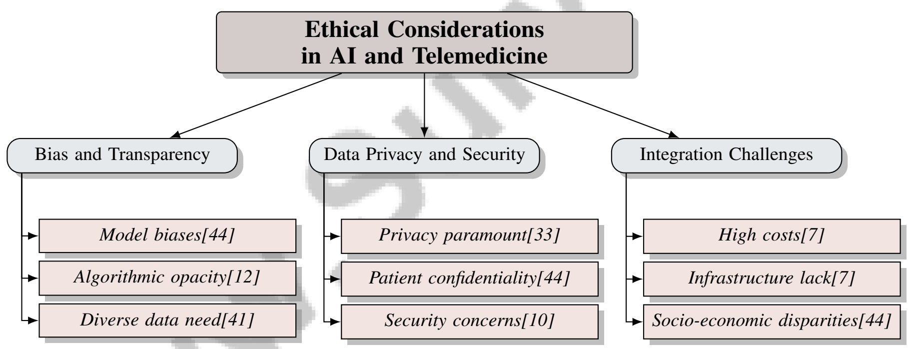

Figure 5: This figure illustrates the key ethical considerations in AI and telemedicine, highlighting issues related to biases, transparency, data privacy and security, and integration challenges. It emphasizes the importance of addressing these concerns to ensure equitable and effective healthcare delivery.

4.4 Enhancing AI Performance through Innovative Techniques

AI advancement in healthcare is propelled by innovative techniques enhancing model performance, interpretability, and scalability. Dynamic and comprehensive datasets are crucial for effective model training. Benchmarks like ChiMed-GPT, employing evolving datasets, provide a more accurate reflection of real-world challenges, improving AI model robustness and adaptability [48].

Integrating interpretability into AI applications is essential. Developing robust frameworks for interpretability, particularly in vision-language models (VLMs) and LLMs, ensures transparency and gains trust among healthcare professionals and patients. Recent advancements in VLMs for healthcare highlight the need for robust evaluation metrics and addressing clinical relevance and ethical considerations in model development [49]. This approach enhances transparency and ensures AI systems provide explainable insights vital for clinical acceptance.

Innovative data processing strategies optimize AI performance. Adaptive algorithms dynamically adjusting data flow and processing in real-time enhance efficiency compared to static methods. This

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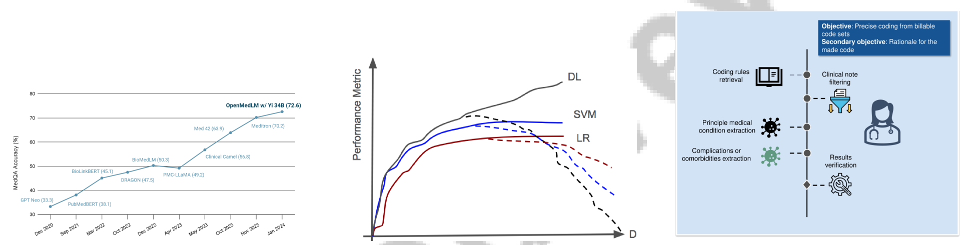
approach tackles unique healthcare AI challenges, facilitating real-time adaptation to fluctuating data inputs and diverse clinical contexts. Such adaptability is crucial for improving diagnostic accuracy, personalizing patient care, and addressing ethical and legal considerations from AI integration in medical practice. Incorporating clinician feedback and ensuring proper training can seamlessly integrate AI tools into existing workflows, enhancing clinician-patient relationships and fostering responsible implementation in high-stakes healthcare environments [36, 44].

Moreover, democratizing access to medical AI technologies is supported by benchmarks ensuring underrepresented communities benefit from AI advancements. This approach promotes equity in healthcare access and fosters AI systems sensitive to diverse cultural and regional needs. The framework proposed by Higgins et al. emphasizes a decision perspective guiding stakeholders through product development phases, addressing clinical, regulatory, data, and algorithmic challenges specific to healthcare [43].

Collectively, these innovative techniques and frameworks pave the way for more effective and equitable AI applications in healthcare, ultimately improving patient care and outcomes. As AI technologies advance, prioritizing transparency, security, and ethical considerations is crucial for responsibly leveraging AI's capabilities in healthcare. This comprehensive approach emphasizes the need for a robust ethical framework addressing data management, human oversight, and algorithmic biases while highlighting the importance of clinician training and stakeholder collaboration. By fostering accountability and interpretability, we can ensure AI applications, including generative AI and medical devices, enhance clinical decision-making while safeguarding patient welfare and equity in healthcare delivery [36, 44, 46, 50, 2].



(a) Improvement in MedQA Accuracy over Time[51]

(b) Performance Metrics of Different Machine Learning Models Over Time[52]

(c) Medical Coding Process Flowchart[53]

Figure 6: Examples of Enhancing AI Performance through Innovative Techniques

As shown in Figure 6, AI is rapidly transforming the healthcare landscape, with innovative techniques continually enhancing its performance and applicability. The first image presents a line graph tracking the improvement in MedQA (Medical Question Answering) accuracy over time, highlighting advancements in models such as OpenMedLM and Med42 from December 2020 to January 2024. This demonstrates significant strides in AI's ability to accurately interpret and respond to medical inquiries. The second visualization compares the performance metrics of various machine learning models, including Deep Learning (DL) and Support Vector Machines (SVM), over different data points, showcasing the evolution of AI techniques in processing and analyzing healthcare data. Lastly, a flowchart detailing the medical coding process underscores the intricacies involved in translating clinical information into standardized codes, emphasizing AI's role in streamlining and enhancing this critical task. Collectively, these examples underscore the transformative potential of AI in healthcare, driven by continuous innovation and improvement in AI methodologies [51, 52, 53].

5 Medical Large Language Models (LLMs) and Vision-Language Models

5.1 Development and Advances in Medical LLMs

Medical large language models (LLMs) represent a pivotal development in healthcare, significantly enhancing clinical decision-making, report generation, and medical education through the analysis of complex medical data. Models like AntGLM-Med-10B demonstrate the efficacy of a structured training process tailored for medical applications, showcasing the potential of LLMs in specific

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Feature	AI-Driven Diagnostics and Treatment Planning	Challenges in AI Implementation	Ethical Considerations in AI and Telemedicine
Purpose	Enhance Decision-making	Address Adoption Barriers	Ensure Ethical Integration
Challenges	Model Interpretability Issues	Black-box Nature	Biases And Transparency
Innovative Techniques	Multimodal Language Models	Not Specified	Great Plea Principles

Table 2: This table provides a comparative analysis of AI-driven diagnostics and treatment planning, challenges in AI implementation, and ethical considerations in AI and telemedicine. It highlights the purpose, challenges, and innovative techniques associated with each area, offering insights into the advancements and obstacles encountered in integrating AI into healthcare. The table serves as a comprehensive overview of the multifaceted dimensions of AI applications in modern medical practice.

healthcare tasks [31]. Similarly, BianCang's two-stage training for traditional Chinese medicine exemplifies the adaptability of LLMs to cater to diverse medical fields [42].

The synergy of vision-language models (VLMs) with medical LLMs extends these capabilities, as evidenced by a comprehensive survey of medical vision-language datasets and architectures [49]. This integration enhances the ability to process multimodal data, improving insight generation from diverse medical inputs. Benchmarks like ChiMed-GPT, with its extensive dataset, are crucial for assessing LLM performance in real-world medical contexts [48].

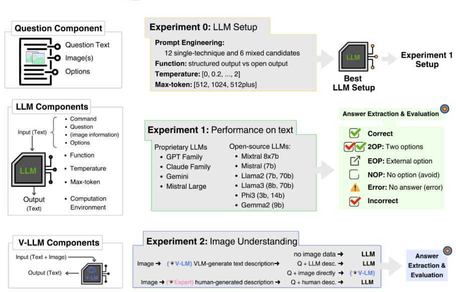
Incorporating auxiliary patient data, such as vital signs and medication history, into LLM frameworks marks a significant advancement, enhancing diagnostic accuracy and treatment personalization [32]. As medical LLMs evolve, prioritizing data diversity and architectural innovation, alongside robust safety frameworks, will be essential to harness their full potential. Addressing biases and ensuring equitable healthcare delivery through diverse representation in LLM development are also critical [54, 55, 56, 57, 53].

5.2 Applications of Vision-Language Models in Healthcare

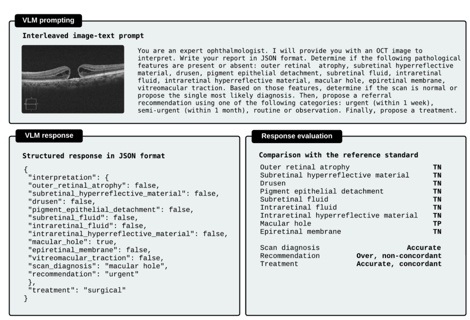
Vision-language models (VLMs) are at the forefront of integrating multimodal data in healthcare, enhancing diagnostic accuracy, treatment planning, and patient management. By synthesizing visual and textual information, VLMs facilitate nuanced understanding of complex medical scenarios, as demonstrated in systematic evaluations of text and image-inclusive questions [58].

VLMs are instrumental in fields like radiology, where they aid in interpreting complex imaging data, thereby refining diagnostic processes [59]. Their application extends to managing respiratory conditions, even in unique environments like microgravity, showcasing their versatility [60]. Open-source frameworks such as the Hippocrates benchmark enhance reproducibility and innovation in VLM applications by providing access to comprehensive training data and evaluation protocols [61].

Datasets like ApolloCorpora, which encompass diverse linguistic and medical characteristics, enrich VLM training, promoting culturally sensitive models that improve patient care [62]. The Aloe benchmark ensures the high quality and relevance of VLMs by focusing on tasks like doctor-patient dialogues and medical image captioning, thus enhancing communication and understanding in clinical settings [63, 64].



(a) Experiment Setup and Evaluation for Question Answering with LLMs[58]



(b) VLM Prompting: Interleaved Image-Text Prompt[65]

Figure 7: Examples of Applications of Vision-Language Models in Healthcare

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As depicted in Figure 7, the integration of Medical LLMs and VLMs has transformed healthcare applications, enhancing diagnostic and decision-making processes. The experimental setup in the first figure highlights the importance of prompt engineering in optimizing LLM performance, while the second figure illustrates how VLMs facilitate the interpretation of complex visual data, supporting informed diagnostic decisions [58, 65].

5.3 Enhancing Clinical Decision-Making with LLMs

Large language models (LLMs) have revolutionized clinical decision-making by providing precise, context-aware insights that improve patient outcomes and optimize healthcare delivery [66]. These models excel in extracting structured information from unstructured data, enhancing patient assessment accuracy and facilitating informed clinical decisions [67]. AntGLM-Med-10B exemplifies this capability, performing competitively in medical question answering and underscoring the effectiveness of targeted training methodologies [31].

The integration of multimodal data through VLMs further enhances diagnostic processes and report generation [49]. The VILA-M3 method, which employs expert models for detailed insights, exemplifies the potential of combining visual and textual data to improve diagnostics [68]. This is particularly beneficial in complex scenarios where traditional methods may fall short.

Fine-tuned language models also excel in extracting social determinants of health (SDoH) from clinical notes, outperforming traditional methods and providing valuable insights for patient care [69]. Despite these advancements, challenges remain in fully integrating LLMs into clinical settings, necessitating ongoing research to address limitations [66]. The development of specialized models, like BianCang for traditional Chinese medicine, highlights the importance of tailoring LLMs to specific domains for superior performance [42].

6 Digital Health Transformation

6.1 Integration with Advanced Technologies

The integration of advanced technologies into digital health is transforming healthcare delivery by enhancing diagnostic capabilities and operational efficiencies. Leveraging multimodal data within large language model (LLM) applications has improved diagnostic accuracy by utilizing diverse data sources [32]. Frameworks like MACDSS, which employ multiple AI agents, refine decision-making in emergency care through the Korean Triage and Acuity Scale (KTAS) [70]. Foundation models for structured electronic health records (EHR) illustrate AI's adaptability, offering scalable solutions for data management and patient care [71].

Innovative algorithms dynamically adjust data processing strategies based on real-time performance, optimizing AI utilization in healthcare [56]. Synthetic data generation enhances training datasets, improving model performance in identifying social determinants of health (SDoH), crucial for comprehensive patient assessments [69]. The Minimum Information for Clinical Artificial Intelligence Models (MI-CLAIM-GEN) provides a robust framework for evaluating AI applications, focusing on data labeling, cohort selection, and ethical standards [72].

Blockchain technology promises enhanced data security and interoperability in digital health, though its application is still maturing [73]. Canonical architectures for predictive analytics, validated through extensive medical claim databases, highlight the need for robust data frameworks to support AI-driven solutions [33]. Dual-stream versus single-stream frameworks in vision-language models (VLMs) underscore the importance of multimodal learning in medical applications [49].

The integration of technologies such as EHRs, telemedicine, AI, and mobile health applications is enhancing healthcare delivery by improving patient outcomes, increasing accessibility, and reducing costs, while addressing challenges like data privacy and interoperability [7, 2, 3, 9, 74]. Future research should prioritize accessibility, interpretability, and adaptability to fully harness these technologies' potential.

6.2 Integration of Machine Learning and EHRs

The integration of machine learning (ML) with electronic health records (EHRs) is advancing modern healthcare by enhancing precision, efficiency, and personalization. ML algorithms extract actionable insights from extensive clinical datasets, improving diagnostic accuracy and treatment outcomes. The ClimedBench dataset exemplifies this integration by utilizing real-world EHRs from leading Chinese hospitals to develop ML models tailored to healthcare [75].

Advanced ML methodologies combining EHR data with imaging features improve model accuracy for segmentation and prognosis, especially in complex cases like head and neck cancers [40]. These algorithms leverage clinical, financial, and demographic data to predict individual treatment responses, facilitating personalized medicine. The EP-MD representation learning method addresses data incompleteness by learning embeddings for both observed and missing data modalities through an affinity graph of patients [76].

Federated learning (FL) preserves patient privacy while enabling collaborative model training across hospitals using local data [77]. The Isthmus platform integrates ML with EHR systems, providing real-time predictive analytics while adhering to HIPAA regulations [78].

Future research should focus on integrating real-time EHR data to enhance ML frameworks' predictive capabilities and address current limitations [79]. Exploring multimodal datasets, additional languages, and health-related tasks could expand ML models' applicability across diverse healthcare settings [80]. Adaptive data processing workflows like ADPP, utilizing real-time feedback, optimize data processing in large-scale ML applications, highlighting the importance of dynamic adaptation in healthcare environments [81]. Such strategies reduce processing delays and enhance throughput [56].

7 Healthcare Innovation and Patient Outcomes

7.1 Impact on Patient Outcomes

Healthcare technology innovations substantially improve patient outcomes by enhancing diagnostic accuracy, treatment efficiency, and overall healthcare delivery. Leveraging diverse patient data within clinical workflows, as demonstrated by Nicolson et al., significantly boosts diagnostic precision, underscoring the importance of integrating multiple data sources for superior patient assessments and outcomes [32]. Advanced frameworks by Suryanarayanan et al. promote collaboration among healthcare teams, facilitating the seamless integration of AI technologies into clinical settings, thus optimizing operational efficiencies and patient care [33].

Machine learning (ML) algorithms play a pivotal role in resource allocation optimization, especially during healthcare crises like pandemics. By utilizing comprehensive data management and real-time analytics, these algorithms enhance patient care by reducing wait times and improving service quality [44, 82, 5]. Interactive ML systems, such as CoachMe, further improve outcomes by supporting healthy lifestyle changes through personalized feedback, thereby reducing chronic disease prevalence in resource-limited settings [9, 82, 83, 84]. The use of electronic health records and wearable devices enhances personalized medicine and care accessibility.

In telemedicine, AI-driven solutions like TrueImage improve teledermatology workflows by enhancing image quality and diagnostic accuracy, crucial for remote consultations. Tools like TrueImage 2.0 have demonstrated improved photo quality, facilitating accurate diagnoses in teledermatology and better patient care outcomes [36, 85, 86, 2, 29]. Innovations in ultrasound robotics, such as the Embodied Intelligence system, illustrate AI's potential in augmenting human capabilities in complex medical procedures by integrating ultrasound technology with large language models (LLMs) to interpret verbal instructions, enhancing scan efficiency and quality [87, 52].

Automated systems like Sporo AI Scribe enhance real-time patient monitoring through efficient transcription and automated data entry into Electronic Health Records (EHRs), minimizing manual errors and improving clinician workflows [34, 38, 88]. Large language models (LLMs), notably the MedTsLLM model, significantly enhance clinical decision support systems by integrating and analyzing complex medical time series data with contextual textual information, thereby improving tasks such as semantic segmentation and anomaly detection in physiological signals [89, 90, 91, 92, 93].

AI-generated, for reference only.

Despite these advancements, challenges persist in ensuring equitable access. Issues like AI algorithm biases, underrepresentation of diverse groups, and the need for robust regulatory frameworks must be addressed to mitigate disparities and ensure all demographic groups benefit from these innovations [1, 9, 94, 54]. Addressing these disparities is crucial for improving health outcomes across diverse populations.

7.2 AI Solutions in Cancer Care

AI integration in cancer care has significantly advanced diagnostic precision, treatment personalization, and patient outcomes. AI technologies are crucial in predicting adverse drug reactions (ADRs) in cancer patients, enhancing safety and efficacy. Abdeldjouad et al. highlight AI's effectiveness in ADR identification, advocating for standardized methodologies and multicenter studies to bolster evidence quality [95]. In head and neck cancer, AI-driven solutions improve diagnostic accuracy and prognostic assessments. Sobirov et al. emphasize advanced architectures and self-supervised learning techniques in enhancing model performance across diverse datasets, essential for tailoring treatments to individual patient profiles [40].

AI's capabilities in processing intricate medical data enhance oncologists' decision-making. By integrating interpretable machine learning and natural language processing, AI improves clinical decision support systems' accuracy and ensures generated insights are understandable and actionable for healthcare professionals. This fosters trust in AI technologies, promoting personalized treatment strategies responsive to patient needs. Ethical AI use and incorporating patient sentiment into treatment plans exemplify AI's transformative potential in creating a more empathetic healthcare environment [6, 17, 2, 96]. Integrating imaging and genomic data provides comprehensive insights into tumor characteristics and treatment responses, optimizing plans and reducing adverse events.

The ongoing evolution of AI technologies in cancer care necessitates continuous research to explore novel applications and enhance existing models. Future research should focus on applying AI methods to diverse datasets, investigating self-supervised learning potential, and developing advanced architectures to improve cancer care delivery and patient outcomes [40]. These efforts position AI as a pivotal force in advancing cancer care, offering new opportunities for personalized treatment and improved survival rates.

7.3 Innovative Solutions for Healthcare Delivery

Innovative solutions in healthcare delivery are transforming traditional models by integrating advanced technologies and methodologies to enhance efficiency, collaboration, and real-time data processing. Platforms like MERLIN exemplify this transformation by offering scalable features that enable rapid processing of large data volumes, effectively addressing various healthcare challenges [5]. The Isthmus platform further illustrates advancements by providing secure, scalable real-time predictive analytics, with future directions including enhanced real-time model training capabilities and expanded functionalities to accommodate diverse data types [78]. This ensures healthcare providers leverage real-time insights to improve patient care and operational efficiencies.

The integration of large language models (LLMs) into healthcare delivery models offers transformative potential. Future research should refine frameworks to address limitations and explore integrating Virtual Simulation Platforms (VSP) and Virtual Doctor tasks to enhance clinical education and training processes [97]. These advancements can significantly improve healthcare professionals' training and preparedness, ultimately enhancing patient care delivery.

The Adaptive Data Processing Platform (ADPP) dynamically adapts to changing data characteristics, reducing unnecessary computations and improving efficiency in data processing, particularly valuable in healthcare environments where data characteristics vary significantly [81]. This capability ensures healthcare systems respond swiftly to evolving clinical demands.

Furthermore, the canonical architecture for predictive analytics developed by Suryanarayanan et al. highlights the importance of robust data frameworks in supporting AI-driven healthcare solutions. Future research will focus on refining this architecture based on user studies and expanding its application to additional healthcare problems, enhancing its utility across various medical domains [33].

Collectively, these innovative solutions represent significant strides in transforming healthcare delivery models. By harnessing advanced technologies like electronic health records, telemedicine, and artificial intelligence, healthcare systems can enhance operational efficiency, adaptability, and collaboration among providers. This integration streamlines patient care delivery and facilitates personalized medicine, leading to improved patient outcomes and cost-effectiveness. However, successful implementation requires addressing challenges related to data privacy, system interoperability, and user comfort, as well as overcoming barriers in data access and governance. Focusing on these areas allows healthcare organizations to fully leverage technological advancements to transform healthcare delivery and enhance patient safety [45, 9, 5].

8 Conclusion

8.1 Challenges and Future Directions

The integration of telemedicine and artificial intelligence (AI) in healthcare presents several pivotal challenges that demand focused research and innovation. Key among these is ensuring the security and privacy of patient data, particularly in the context of cloud-based telemedicine platforms. Future research should aim to fortify security measures, reduce operational costs, and enhance user experience in augmented reality (AR) healthcare applications. This is especially pertinent with the rise of advanced technologies such as 6G and AI within the Internet of Medical Things (IoMT), which necessitate intelligent resource management and robust security protocols.

Interoperability and seamless data integration across varied healthcare systems remain significant hurdles. Developing comprehensive frameworks to facilitate effective data exchange and improve model interpretability is crucial for the successful deployment of AI-driven healthcare solutions. Research efforts should also be directed towards optimizing large language models (LLMs) and assessing the impact of prompt engineering on AI's performance in healthcare settings. Addressing biases in training data and refining AI models to enhance interpretability are essential for building trust and acceptance of AI technologies in clinical environments.

Ethical considerations surrounding generative models and multimodal data in healthcare call for the establishment of strong ethical frameworks. The FUTURE-AI framework provides a structured approach to addressing these ethical challenges, focusing on clinical, technical, ethical, and legal aspects. Future initiatives should prioritize developing frameworks that ensure responsible AI deployment in personalized medicine and telehealth, fostering human-AI collaboration, and tackling privacy concerns. Engaging a diverse range of stakeholders is imperative to refine these frameworks and address ethical issues related to autonomy and equity.

Another critical area for future research is enhancing the adaptability of AI models to cover a broader spectrum of medical domains and improve robustness. It is crucial to refine model selection algorithms and enhance the adaptability of AI systems to expand their applicability across various medical fields. Investigating the integration of AI models into clinical workflows and methods to bolster model robustness and generalizability is also necessary. Incorporating genetic data into predictive models can lead to more personalized treatment recommendations, thereby improving healthcare solutions.

Cultural sensitivity and patient agency are vital considerations in AI development. Research should advocate for structural changes that prioritize these aspects, ensuring that AI technologies are personalized and culturally attuned. Broadening analyses to include a wider range of patient demographics can enhance the effectiveness of medical devices and interventions across diverse populations.

Finally, future research should explore the broader applications of text data in observational studies and randomized experiments to validate findings across various clinical contexts. Future directions include enhancing interpretability, optimizing computational efficiency, and expanding model capabilities to encompass additional tasks such as forecasting and clustering. Addressing these challenges and exploring future research avenues will be crucial in advancing telemedicine and AI technologies, ultimately enhancing healthcare delivery and patient outcomes. Future efforts should also focus on expanding the framework's capabilities, fostering community contributions, and collaborating with other healthcare AI initiatives to unify the ecosystem.

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