Generative AI for Transformative Healthcare: A Comprehensive Study of Emerging Models, Applications, Case Studies, and Limitations

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ABSTRACT Generative artificial intelligence (GAI) can be broadly described as an artificial intelligence system capable of generating images, text, and other media types with human prompts. GAI models like ChatGPT, DALL-E, and Bard have recently caught the attention of industry and academia equally. GAI applications span various industries like art, gaming, fashion, and healthcare. In healthcare, GAI shows promise in medical research, diagnosis, treatment, and patient care and is already making strides in real- world deployments. There has yet to be any detailed study concerning the applications and scope of GAI in healthcare. Addressing this research gap, we explore several applications, real-world scenarios, and limitations of GAI in healthcare. We examine how GAI models like ChatGPT and DALL-E can be leveraged to aid in the applications of medical imaging, drug discovery, personalized patient treatment, medical simulation and training, clinical trial optimization, mental health support, healthcare operations and research, medical chatbots, human movement simulation, and a few more applications. Along with applications, we cover four real-world healthcare scenarios that employ GAI: visual snow syndrome diagnosis, molecular drug optimization, medical education, and dentistry. We also provide an elaborate discussion on seven healthcare-customized LLMs like Med-PaLM, BioGPT, DeepHealth, etc.,Since GAI is still evolving, it poses challenges like the lack of professional expertise in decision making, risk of patient data privacy, issues in integrating with existing healthcare systems, and the problem of data bias which are elaborated on in this work along with several other challenges. We also put forward multiple directions for future research in GAI for healthcare.

INDEX TERMS Generative AI, ChatGPT, healthcare, LLMs, applications.

I. INTRODUCTION

Tools based on artificial intelligence have gradually increased in recent decades, and generative AI has emerged as a powerful tool within this landscape. Generative AI combines machine learning techniques, deep neural networks, and natural language processing (NLP) to learn patterns and characteristics from vast datasets and generate outputs that resemble human-generated content. The output can be generated in various forms, such as audio, video, and text, depending upon the demand. ChatGPT, developed by Open AI, is a language model capable of generating human-like

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responses to text inputs. It is built upon a transformer model and is one of the most popular GAI models [1]. GAI models such as DALL-E [2], Midjourney [3], and Stable diffusion [4] are capable of generating high-quality images from textual prompts. These GAI models also showcase the ability to bridge the gap between modalities [5] and aid education [6]. The GAI technology has shown promising potential in healthcare. It can revolutionize how we approach medical diagnosis, treatment, and patient care. The GAI models can assist healthcare professionals in making clinical decisions in various fields such as urology, radiology, and cardiology [7]. A very recent survey by Market.us [8] predicts that GAI in the healthcare industry is set to reach around $17 billion by 2032, primarily driven by the automation in healthcare operations of medical imaging and diagnostics and drug discovery and development.

To generate reliable results in healthcare, GAI models need to train on a large volume of medical data, including patient records, medical images, and genomic sequences. These trained models can provide innovative solutions to traditional problem-solving and augment healthcare pro- fessionals' capabilities to enhance patient outcomes. GAI models can also simulate and predict disease progression, thus further helping in better understanding and monitoring. A study by Messiah et al. indicates the reliability of such models. The GAI model was able to answer all queries regarding typical clinical toxicology cases of acute organophosphate poisoning [9]. The GAI technology can also be used in disease management and risk assessment, as well as to increase research education and drug development. It has opened the windows to innovative healthcare using technology [10].

One of the major areas where GAI is making a significant contribution to healthcare is medical imaging. GAI models like DALL-E can assist in detecting and diagnosing diseases by analyzing patient medical images, such as X-rays, MRIs, and CT scans. GAI algorithms can be trained to learn and identify subtle patterns and anomalies in scans that often slide past the naked eye. By using generative models, timely interventions and improved patient care can be provided. With higher accuracy and speed, this technology helps in early disease detection, such as cancer or neurodegenerative disorders. Furthermore, GAI can augment healthcare research and education. The models help in experimentation and hypothesis by generating synthesized data. They can produce virtual patient scenarios, enabling more practical education for healthcare professionals. GAI models can help Biomarker identification by analyzing large-scale genomic, proteomic, or imaging data. They facilitate research and study by generating synthetic data on which medical researchers can perform experimentation. GAI models can generate synthetic data samples that exhibit specific biomarker characteristics to help study pathology, which helps researchers visualize complex medical data and facilitate exploratory analysis for better understanding.

In addition to medical imaging and research, GAI has various other applications, including drug development, chatbots, personalized patient treatment, medical simulation and training, clinical trial optimization, and mental health support. Healthcare professionals can use various GAI mod-els like ChatGPT for assistance in diagnosis and treatment. It is seen that GAI models like ChatGPT can learn and identify their own mistakes just by prompting it to check if any output is wrong. These models can also generate patients' discharge summaries by leveraging a large amount of data they are trained on and by analyzing patient data and their medical records. They can do so without any detailed description or meaning of medical terms provided beforehand. This paper discusses how these and other generative models can enhance the healthcare system.

The integration of GAI and healthcare also presents multiple challenges. Data privacy, ethical considerations, and data bias are critical aspects that need attention in this GAI- healthcare confluence to utilize the technology's full potential while ensuring patient safety and security. Therefore, in this work, the contributions are summarized as follows: 1. Discuss how GAI can support healthcare systems, highlighting their limitations and how to overcome them. 2. Analyze some real-world GAI models in healthcare systems. 3. Provide a variety of applications of GAI in healthcare. 4. Describe four real-world scenarios of using generative AI in healthcare. 5. Discuss seven healthcare-customized GAI models. 6. Present several limitations and future directions on the applications of GAI in healthcare.

A. ORGANIZATION

The rest of the paper is organized as follows. Section II provides a brief overview of generative AI. Section III presents an analysis of the real-world performance of GAI models in healthcare. In Section IV, we provide and elaborate on a variety of applications of GAI in healthcare.Section VI describes four real-world scenarios of using generative AI in healthcare - visual snow syndrome, molecular optimization, medical education, and dentistry. Section V discusses seven healthcare-customized GAI models. Sections VII and VIII present limitations and future research directions on GAI applications in healthcare, respectively. Finally, the review is concluded in Section IX.

II. AN OVERVIEW OF GAI

Generative AI is an advanced artificial intelligence tech-nology that has recently gaining significant attention and corporate funding. Its popularity has led to different startups being formed solely on the development of GAI technol- ogy [11]. In response to user prompts, GAI models can generate various forms of media, including text, images, audio, video, and 3D models. This cutting-edge technology harnesses the power of pattern recognition and learns from existing data to generate novel and distinctive results that closely resemble the characteristics of the input trainin data. GAI has rapidly gained popularity and is now widely regarded as one of the most coveted technologies in the world. What sets GAI apart is its ability to produce realistic and coherent outputs. Unlike traditional AI systems designed for specific tasks, GAI surpasses rule-based and deterministic approaches. It extensively utilizes advanced machine learning techniques such as Deep Learning (DL), Natural Language Processing (NLP), and Neural Networks. These techniques enable systems to discern patterns and traits from vast training datasets, empowering them to generate new data that closely resembles the original information. GAI models are unique, showing enhanced creativity and novelty in generating data. The data produced is not just a copy of training data but something different with its original traits. They can train on unlabeled data and map underlying patterns and structures independently. This ability of unsupervised learning makes GAI models valuable when labelled data is scarce.

GAI models have seen a sharp rise in usage and production. Over time, GAI models have become more sophisticated, employing complex architectures with improved stability and quality in generating realistic data in different modalities. Techniques like conditional generation in GANs and fine- tuning language models enable more precise and controllable content generation.

Noteworthy examples of GAI systems include ChatGPT, Dall-E, Midjourney and Bard. ChatGPT, developed by OpenAI, is one of the most popular GAI models known for its natural language processing capabilities. It engages users in coherent and contextually relevant conversations.

Large Language Models (LLMs) represent a transforma- tive breakthrough in natural language processing (NLP), marked by their immense scale, complex architecture, and remarkable language generation capabilities. ChatGPT is a generative pre-trained transformer and belongs to the family of large language models. GPT utilizes a decoder- only transformer architecture. This architecture enables it to probabilistically generate sequences of words or tokens, given an input prompt or context. The model predicts the most likely sequence of words following the input based on the patterns learned during training. It relies heavily on self-attention mechanisms. The transformer architecture facilitates the model's ability to process sequential data efficiently by simultaneously attending to different parts of the input sequence. This mechanism allows the model to capture dependencies and relationships between words in long-range contexts, which is crucial for understanding and generating coherent text. Notably, the technical prowess and generative prowess of GPT have set new benchmarks in the field, showcasing its adaptability and performance without extensive fine-tuning for specific tasks. GPT models, such as GPT-3 [12], have enormous parameters, often in the billions, allowing them to capture intricate linguistic nuances and context. This large parameter count contributes to their ability to generate diverse and contextually relevant text across various domains. However, LLMs' scale and computational demands, like GPT, pose challenges regarding resource requirements and potential biases inherited from the training data. Further research is ongoing to optimize these models for efficiency and mitigate biases. Nevertheless, the advent of Large Language Models, particularly exemplified by GPT, stands as a monumental advancement in machine learning, revolutionizing the capabilities of NLP systems and paving the way for increasingly sophisticated language understanding and generation technologies.

Figure 1 displays existing GAI models. As the figure shows, GAI models can generate various data types such as audio, video, text, images, 3D visual and code. These GAI models can generate intricate content that mirrors human creativity. This characteristic makes GAI an invaluable tool which can be used in various industries, including gaming, entertainment, and product design. Over the past decade, this has led many multinational corporations like Google, Microsoft and numerous smaller firms to invest in actively developing and refining this technology. Dall-E is another GAI model developed by OpenAI. It produces images based on textual prompts. Its potential can be extended into healthcare in many ways. It can be used in medical imaging to assist radiologists and clinical workers, as this model can be trained on different medical image data and their textual descriptions and generate relevant synthetic data. It is important to note that GAI is a rapidly evolving field with ongoing research and experimentation to develop this technology further.

III. REAL WORLD GAI PERFORMANCE IN HEALTHCARE

GAI has shown great development in recent years, demon- strating remarkable capabilities in various applications, from text to images. However, while GAI has shown great promise in controlled environments, assessing the GAI models in real-world scenarios is essential to test the model's reliability and effectiveness. While evaluating the performance of GAI models outside a controlled model, several factors need to be considered, including the reliability of outputs, bias and fairness, generalization across different populations, interpretability, and the potential impact on human decision-making. Testing requires rigorous evaluation methodologies and comprehensive datasets.

An evaluation was done on ChatGPT, a large language model (LLM) by Kung et al. [13].They tested ChatGPT to answer the United States Medical Licensing Exam (USMLE) questions. The test was conducted in three stages of standardized tests, and ChatGPT could pass all the stages without specific training or reinforcement. It is important to note that these tests were of expert-level knowledge, and ChatGPT was able to pass with 60% accuracy. Furthermore, the answers provided by ChatGPT did not require any specialized input and were detailed while including clinical insights and comprehensive reasoning.

Another evaluation was done on ChatGPT 4 [14], an upgraded version of ChatGPT by Teebagy et al. [15].

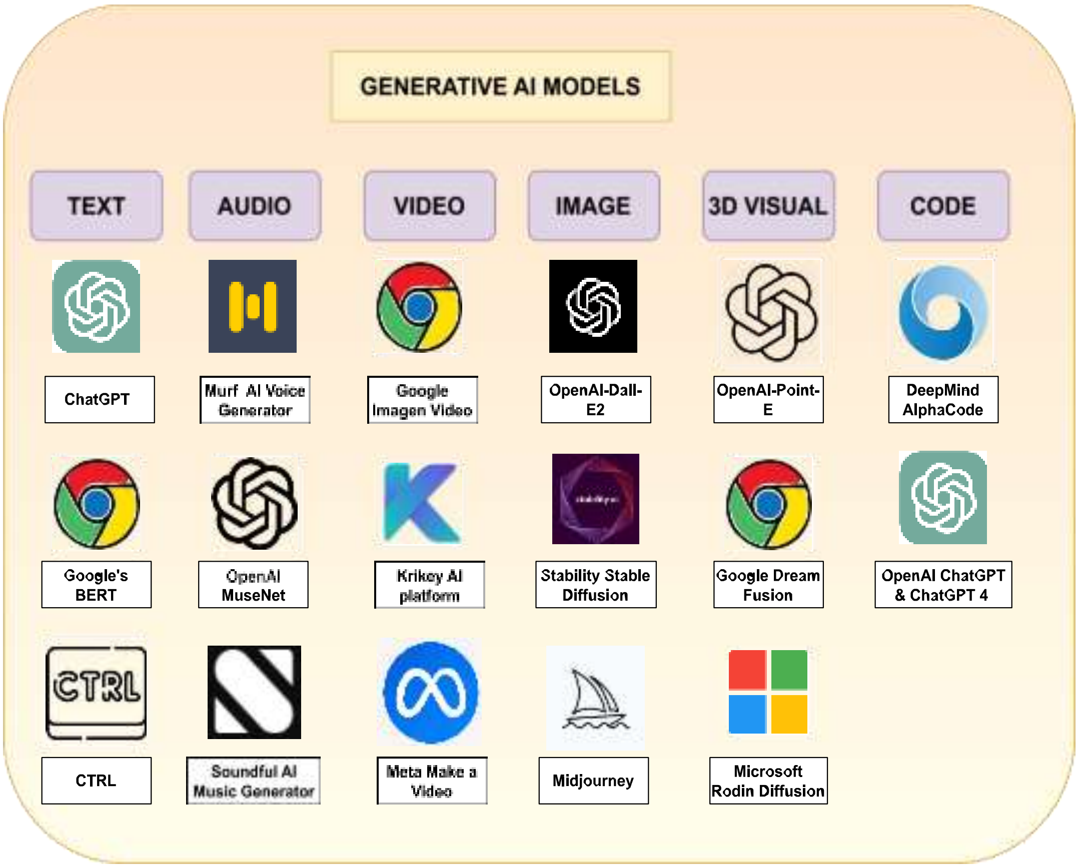

FIGURE 1. Popular GAI models.

They tested the model on the Ophthalmology Knowledge Assessment Program (OKAP) examination conducted by the American Academy of Ophthalmology (AAO) to assess residents' knowledge of ophthalmology training programs. The examination consisted of 180 questions and con- tent of questions ranging from anatomy and physiology to ophthalmic subspecialties such as cornea and neuro- ophthalmology [16]. Results indicated that ChatGPT 4 could pass the examination and outperform its predecessor, ChatGPT 3.5, thus establishing the growing potential for using GAI models in healthcare consultation and treatment. ChatGPT also passed the radiology board-style examination nearly [17]. The examination of 150 questions without images of multiple choice answers was conducted with the questions of the difficulty level of Canadian Royal College and American Board of Radiology examinations. ChatGPT gained an overall score of 69% by correctly answering

104 questions out of 150. It showed better performance in clinical management questions and low-order thinking questions. Table 1 shows that GPT 4 can handle multi- level prompts, perform complex analysis and provide more detailed results compared to its predecessor ChatGPT-3 [18]. The performance evaluation of ChatGPT showed the potential reliable use of GAI in healthcare. With the GAI models currently evolving and under rigorous research and development, it opens a wide window for integrating various GAI models in the daily dealings of healthcare professionals.

The GAI technology will soon be positioned to be a part of regular clinical practice, contributing in various lengths, accounting for its wide applications in various healthcare fields, and enhancing patient care.

IV. APPLICATIONS

This section discusses the applications of using GAI in different healthcare spheres. Figure 2 presents an overview of the discussed applications.

A. *MEDICAL IMAGING*

Medical imaging is a rich and non-invasive technique that provides healthcare professionals with a detailed visual- ization of the patient's anatomical structures for treating medical conditions. This technique enables early detection of diseases, improves screening procedures, and guides treatment planning strategies. In the current scenario, med- ical imaging faces many limitations, such as insufficient annotated data and limited imaging modalities and contrast. GAI has emerged as a promising solution to address these challenges and further enhance medical imaging capabilities.

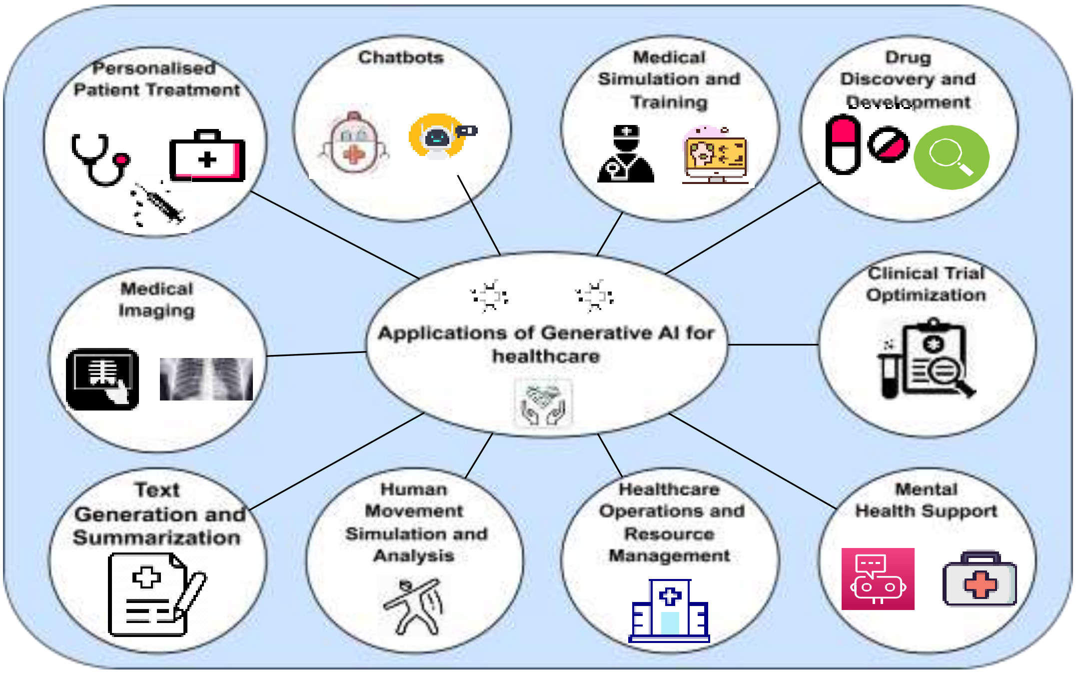

FIGURE 2. Applications of Generative AI in Healthcare.

1) DATA AUGMENTATION

It is often challenging to train deep learning models as the datasets available in medical imaging are limited. GAI techniques, such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), provide a reliable solution as they can generate synthetic images that resemble patient data, increasing the models' robustness. GAI models are also capable of generating data on rare conditions such as Aquagenic Urticaria [19], methemoglobinemia [20] and generate missing data, thus providing an augmented and diverse dataset for training and evaluation, enhancing the ability to detect and diagnose diseases in real-world scenarios. It is observed that while GAI methods like GANs and VAEs play a pivotal role in addressing limited annotated data in medical imaging, the extent of their utilization might vary due to the prevalence of scarce datasets for rare conditions.

2) IMAGE ENHANCEMENT AND RECONSTRUCTION

One of the essential elements in disease diagnosis through medical imaging is the image quality of scans such as an X-ray or CT scan. When this image suffers distortion due to noise, missing data, and low resolution, it can lead to misin-terpretations and delays in the diagnosis. GAI models can be trained to remove noise from these images using frameworks such as generative adversarial networks and autoencoders; this improves the accuracy of quantitative analysis, allowing reliable measurements and quantitative parameters that eventually aid in assessing disease progression, longitudinal monitoring and treatment response. Diffusion-based model DiffMIC [21] is tailored for medical image classification. It focuses on eliminating noise and perturbations while robustly capturing semantic representations. DiffMIC uses a dual conditional guidance strategy that enhances step-wise regional attention by conditioning each diffusion step with multiple granularities. Additionally, this study [21] proposes a method to learn mutual information within each granularity by enforcing Maximum-Mean Discrepancy regularization during the diffusion forward process. GAI models can also produce high-resolution images from low-resolution data by applying a super-resolution approach. The super-resolved images are used for accurate disease diagnosis and detailed study of the anatomical structures. Bing et al. [22] used an enhanced generative adversarial network for the super-resolution reconstruction of images. The authors improved the squeeze and excitation blocks in GANs generator and discriminator by strengthening important features and weakening the non-important ones. Furthermore, they used low function loss to train the model by combining L1 loss, mean square error loss, perceptual loss, and relativistic adversarial loss.

Furthermore, challenges like varying sequence lengths, missing data or frames, and high dimensionality pose sig-nificant hurdles for conventional models. A novel approach called Sequence-Aware Diffusion Model (SADM) [23] is introduced for generating longitudinal medical images to address this challenge of modeling the dynamic anatomy of the human body, which can be influenced by both long-term (e.g. chronic diseases) and short-term (e.g. heartbeat). It introduces a sequence-aware transformer as the conditional module within the diffusion model. This innovative design enables learning longitudinal dependencies, even amidst missing data during training. Furthermore, it enables the autoregressive generation of image sequences during infer- ence, offering a more comprehensive insight into anatomical changes over time.

3) CROSS-MODALITY IMAGE TRANSLATION

There are many ways to perform medical imaging. These methods include techniques such as X-ray, positron emission tomography (PET), magnetic resonance imaging (MRI), computed tomography (CT), ultrasound, and Single-Photon Emission Computed Tomography (SPECT), to name a few. These different techniques are called modalities. Each modality uses different physical properties and imaging techniques to generate images; each has different advantages and limitations regarding image quality, spatial resolution, sensitivity, and contrast.

Cross-modality image translation converts medical images from one modality to another while preserving relevant fea- tures. This enables the fusion of modality-specific advantages and complementary information; it addresses data limitations and offers clinical flexibility. This flexibility allows several diagnostic choices, but it is a challenge to translate infor- mation from one modality to another. GAI techniques, such as generative adversarial networks (GANs) and variational autoencoders (VAEs), have shown remarkable capabilities in cross-modality image translation. They excel at learning the complex mapping between different image modalities. They preserve underlying structural and pathological information, facilitating accurate cross-modality translation. Generative AI also helps overcome modality-specific limitations, such as if a modality has spatial resolution or contrast issues. GAI can transform images from higher resolution or contrast modality to enhance visualization. It helps healthcare professionals make more clinically informed decisions; they can leverage the benefits of multiple modalities to produce advanced imaging to facilitate diagnosis and treatment.

Generative AI-based cross-modality translation opens up new avenues for research and innovation in medical imaging. It has proved useful in generating synthetic images, preserving important information, promoting research and innovation, and fusing inter-modality data. The GAI has unlocked the full potential of diverse image modalities by which healthcare professionals can make better diagnoses and devise personalized patient treatment strategies.

4) INTERPRETABILITY AND EXPLAINABILITY

GAI models help achieve interpretability and explainability in medical imaging [24]. Deep learning models often lack this, making understanding the reasoning behind their predictions challenging. Interpretability refers to the ability to understand and explain the decision-making process of the AI model. In medical imaging, interpretability is crucial because healthcare providers and patients must trust and understand the generated results to proceed with treatment and make informed decisions [25]. Various methods can achieve this [26], the most important being visualization. Learning features are visualized to understand which image regions or characteristics influence the generated output. For this, attention mechanisms are also used, explicitly highlighting the important regions or features that contributed to the output; this provides transparency and a clear understanding to healthcare professionals as to why certain areas are emphasized. Explainability tells the user why a specific decision was made by providing a clear and coherent explanation. It makes the decision-making process more transparent and easy to understand for the users, allowing them to put better trust in the model. Some explainability techniques help the model achieve this. Local explanation focuses on explaining the decision on a specific image instance; this helps understand the model's decision at every level. Keeping the model architecture and decision-making process simple and transparent can enhance explainability. GAI aids in achieving interpretability and explainability, which are crucial for trust and understanding in medical AI. Techniques such as attention mechanisms and local explanations contribute to transparency; however, ensuring a balance between model complexity and explainability remains challenging.

B. *DRUG DISCOVERY AND DEVELOPMENT*

Drug development is associated with bringing new therapies to the market. It is a complex and time-consuming process involving high costs and low success rates. GAI offers a promising solution to the de novo design of molecular structures. It can generate novel compounds, optimize drug candidates and predict the properties of drugs. GAI is capable of 1D, 2D and now 3D models of molecules [27]. Inception Score (IS) was proposed by Salimans et al. for generative models [28], which investigates if the generated molecules can be classified correctly to cover the chemical space defined by the training set.

Among various challenges in drug development is the prediction of protein function, an area that has seen significant advancement through various machine-learning approaches in recent years. However, prevalent methods often frame this task as a multi-classification problem, assigning predetermined labels to proteins. Prot2Text [29] is a novel approach that departs from the traditional binary or categorical classifications by predicting protein functions in a free-text format. This innovative methodology employs an encoder-decoder framework that integrates Graph Neural Networks (GNNs) and Large Language Models (LLMs). Through this amalgamation, diverse data types, including protein sequences, structures, and textual annotations, are effectively assimilated, ensuring a comprehensive repre- sentation of proteins' functions and generating detailed and accurate descriptions. To evaluate the efficacy of Prot2Text, a multimodal protein dataset was curated from SwissProt, demonstrating its effectiveness through empirical

TABLE 1. Performance of GPT 4 over ChatGPT based on user prompts.

Prompts	ChatGPT	GPT 4
Prompt 1: Diagnosing a patient showing ambiguous symptoms	A Patient presents with occasional dizziness, weight loss, fatigue and low blood pressure. What are some possible causes of these symptoms?	A 30 year old female with a 2 month history of unintentional weight loss of about 10 pounds, progressive fatigue and episodes of dizziness. Please provide differential diagnosis and suggest relevant diagnostic tests.
Prompt 2: Patient education	Explain Tuberculosis in simple terms.	Create a patient friendly handout on tuberculosis, including an overview of the condition, symptoms, risk factors, potential complications, and management strategies.
Prompt 3 – Reviewing medical research	Tell me about the benefits of exercise in improving mental health.	Define the relationship between physical exercises and mental health by summarizing recent research findings. Include the influence of different types of exercise and recommendations for various populations.

analysis. The results underscore the transformative potential of multimodal models, particularly the fusion of GNNs and LLMs, which equips researchers with potent tools for precise predictions of proteins' functions.

The GAI also assists in understanding the structure- activity relationship (SAR) of the molecules. It generates a diverse set of molecules and studies how the activity changes corresponding to their structure which helps researchers get insights into chemical features essential for drug-target interactions.

The GAI also facilitates generating new molecules with different core structures while retaining key pharmacophoric features known as scaffold hopping. It enables the researchers to explore the chemical space beyond existing scaffolds, potentially leading to improved drug candidates with differ- ent properties and mechanisms of action.

C. PERSONALIZED PATIENT TREATMENT

GAI has advanced significantly in personalized patient treatment, evolving from initial predictive modeling to integrating specific conditions for tailored treatment plans. Conditional Variational Autoencoders (CVAEs) are GAI models that combine conditional variables and variational autoencoders to learn latent patient information while incorporating specific conditions relevant to personalized treatment. By altering values of different conditions, the model generates various treatment plans tailored to individual patients [30]. Fine-tuned NLP models such as Bidirectional Encoder Representation from Transformers (BERT) have improved in generating personalized treatment summaries and adaptive plans based on patient data.

D. MEDICAL SIMULATION AND TRAINING

Medical trainees and professionals must refine their clinical skills in a controlled environment; this is done via medical simulation. Realistic and immersive experiences of real- life critical conditions can be simulated using GAI. GAI techniques such as virtual patient simulation, procedural simulations, scenario generation, and haptic feedback can transform medical education.

GAI models can be employed to generate virtual avatars of patients. These avatars resemble closely to the patients and can be customized by adjusting parameters such as age, gender, and medical history, allowing for a more realistic experience. StyleGAN2 (Style-based Generative Adversarial Network) model can generate high-resolution images with realistic details; these models can be adapted to generate virtual avatars of the patient [31]. By incorporating data from physiological models and clinical knowledge, the GAI can create fundamental changes in organ function, vital signs and disease progression over time by capturing the temporal dynamics and complications associated with specific conditions. It not only helps medical professionals simulate complicated surgery but also helps train medical students. The generative models can expose healthcare professionals to a wide range of patient cases, sudden dete- rioration, and adverse reactions. The different scenarios are designed to train them to handle complex and unpredictable situations, enhancing their decision-making skills and clinical competence. The generative models can generate rare and uncommon conditions; this allows students to Gain exposure and develop proficiency in dealing with such cases.

GAI models can generate realistic haptic feedback by analyzing visual and contextual information. The haptic signals mimic the tactile sensations experienced during medical procedures. The generative models can also generate 3D representations of organs, bones, or blood vessels, which can be integrated into haptic feedback systems allowing professionals to interact with and manipulate them as if they were real.

E. CLINICAL TRIAL OPTIMIZATION

Introducing and evaluating new interventions and translating research findings into clinical practice is essential. They allow head-to-head comparisons of different treatment options, providing researchers with valuable evidence for choosing the most appropriate treatment for specific patient populations. However, the complexity and challenges of recruiting a diverse patient pool while ensuring safety make clinical trials tedious. GAI presents a transformative approach to address these complexities and optimize clinical trials. GAI helps advance protocol design and validation for clinical trials [32]. It does so by simulating virtual trials with different designs, randomizing strategies or building an inclusion criterion. GAI helps researchers reduce biases, predict treatment responses based on patient characteristics, and simulate different scenarios. Generative models like DeepSurv and DeepHit can predict patient responses based on different patient characteristics and genetic information; these models can evaluate the potential outcomes of different interventions, which aids professionals in understanding how different subgroups react to specific conditions. GAI helps estimate sample size for clinical trials by running multiple iterations of simulated virtual clinical trials using synthetic patient populations. Gootjes-Dreesbach et al. [33] proposed a new approach for clinical trials using longi- tudinal clinical study data by employing the Variational Autoencoder Modular Bayesian Network (VAMBN) model. Virtual patient data was generated while making theoretical guarantees on data privacy. It could help in trial design and facilitate data sharing. The GAI can successfully select and optimize endpoints for clinical trials. It can identify clinical outcomes and endpoints by analyzing historical data and meaningful patterns for patients, researchers and regulatory agencies. The GAI in clinical trial optimization can significantly enhance trial efficiency, improve patient stratification, reduce costs and generate reliable and gener- alizable evidence. Researchers can optimize trial protocols using the GAI to personalize treatment and improve patient care.

F. MENTAL HEALTH SUPPORT

Mental health is of utmost importance in leading a healthy and peaceful life. Any disruption in mental health directly impacts the overall well-being of an individual. Today, problems like anxiety, frustration, and depression are com- mon worldwide. The GAI is a tool that can help the stressed population to improve their quality of life. The GAI gives personal treatment plans and therapy based on individual needs. They can perform sentimental analysis by analyzing text and speech patterns and detecting sentimental and emotional cues. The GAI contributes to the early detection of mental health conditions by analyzing large volumes of data and identifying patterns and indicators suggestive of specific mental health conditions and can flag individuals who may be at a higher risk or may require immediate assistance. Yang [34] use generative adversarial networks and hierarchical attention mechanisms to diagnose depression using multi-modal data, including text and audio physiological signals. Generative AI can generate an immersive virtual reality environment for mental health patients, providing a safe time off from the real world [35]. A correct dosage of this can significantly improve their conditions; the virtual reality environment can simulate exposure therapy, relaxation techniques and stress management scenarios. By leveraging GAI capabilities, mental health support can be more accessible, effective and personalized. With human oversight, the GAI can augment existing mental health services. Therefore, Leveraging GAI capabilities augments existing mental health services, making them more accessible, effective, and personalized. With human oversight, GAI tools can supplement and enhance mental health support by providing tailored interventions, ultimately aiding in improving the overall well-being of individuals [36].

G. HEALTHCARE OPERATIONS AND RESOURCE MANAGEMENT

Healthcare operations and resource management are complex and multifaceted areas which involve various aspects such as resource allocation, demand prediction, workflow opti- mization, and much more. Largely, these tasks are driven by human decision-making, which can be time-consuming and prone to errors; given the medical aspect, it can also be fatal in some instances. However, with the advent of GAI models, healthcare organizations can harness GAI's power to make data-driven decisions and enhance operational efficiency. A generative model, DALL-E, can be used to generate visual representations of healthcare facility layouts and floor plans to help identify areas of improvement, streamline workflows and ensure optimum utilization of space and equipment. It can improve communication and understanding by generating visual aids for patients with specific needs or language barriers. It also generates illustrations for standard operating procedures (SOPs) or guidelines on different healthcare conditions to train staff and ensure consistent practices. Another generative AI model, ChatGPT, can assist in operations management by scheduling appointments with patients, integrating with hospital information systems, and providing real-time updates on wait times. GAI models can automate routine decision-making processes such as approving and denying and even recommending [37] differ- ent procedures based on predefined criteria or conditions, reducing administrative burden and enabling a faster response time.

H. MEDICAL CHATBOTS

One of the significant applications of GAI has been the development of medical chatbots. Chatbots are versatile computer programs designed to simulate human conversation and automated responses. They can serve as virtual assistants for patient support and engagement. They can answer common questions, offer guidance and provide medication reminders. ChatGPT, based on the GPT (Generative Pre- trained Transformer) architecture, can be trained on a wide range of healthcare data, enabling it to provide accurate and consistent responses to patient queries. Dave et al.. [38] discuss various applications of ChatGPT in medicine, including its aid to patients as a virtual assistant and record keeping of patient files. Patients usually seek information about any symptom they are showing or a specific medical condition; ChatGPT can offer preliminary guidance by asking relevant questions. Based on the information provided by the patient, ChatGPT can assess the urgency and severity of the symptom and provide general information about potential causes and common conditions associated with those symptoms, self-care measures and when to seek medical attention; in this way, they assist in triage and symptom assessment.

Chatbots can be a reliable source of health information and education; they can explain medical terms Moreover, it offers guidance on various health topics. Information provided by ChatGPT is reliable as it passed the United States USMLE, [13] which is a medical licensing exam; the exam was con- ducted in three levels, in which ChatGPT could perform near the passing threshold and gave answers with concordance and insights in its explanations. Lee [39] explores the potential of ChatGPT in medical education as a virtual assistant to teach medical students and increase their engagement and learning. Recently, DiagnaMed Holdings Corp. released Dr GAI, a GAI medical chatbot based on ChatGPT, which helps people in a general health advisory. Dr GAI is the third com- mercial product from the company's Health GAI division, which focuses on building generative AI applications for healthcare.

Another chatbot, InstructGPT [40], a ChatGPT variant, can provide step-by-step instructions to patients. It is advanta- geous in providing medication administration instructions to patients. It can generate step-by-step guides on administering different medications, including information from opening packages to measuring dosages and using specific medical devices such as syringes or droppers. InstructGPT can also generate medical schedules for patients depending on their prescriptions. However, it is essential to note that chatbots like ChatGPT and InstructGPT should only work as a tool for assistance under clinical supervision. Seeking proper medical guidance from certified healthcare professionals is essential in all medical conditions. Hence, GAI-driven medical chatbots emphasize their versatility as virtual assistants, aiding in triage, providing reliable health information, supporting medical education, guiding patients in medication administration, and highlighting the necessity of clinical supervision in all medical conditions. At the same time, while GAI-powered chatbots are beneficial as assistance tools, they should always operate under clinical supervision.

I. HUMAN MOVEMENT SIMULATION AND ANALYSIS

Understanding human movements is vital to get a detailed picture of the dynamic anatomy of the human body. Human movement simulation and analysis can be performed using GAI technologies and get valuable insights into diagnostic, therapeutic, and performance-based optimization processes. Healthcare professionals can significantly improve treatment planning and patient care by carefully analyzing human body movements. Generative models utilize advanced machine-learning techniques to simulate human movement with remarkable accuracy and detail.

Midjourney can simulate movements tailored to individual patients' needs, helping in virtual rehabilitation and physical therapy sessions. It can provide interactive guidance and visual demonstrations of correct movement techniques. This allows better patient engagement and rehabilitation outcomes. GAI models also help assess gait abnormalities, analyze movement patterns and guide rehabilitation strategies for individuals with mobility impairments, enabling tailored interventions and objective progress monitoring.

By leveraging Midjourney and similar GAI models in human movement simulation and analysis, healthcare profes- sionals can access a powerful tool that accurately simulates realistic movements, enhancing their understanding of move- ment patterns and contributing to better patient care.

J. INSURANCE PRE-AUTHORIZATION/PRIOR AUTHORIZATION

Pre-authorization, also known as prior authorization or pre-approval, is a mechanism that healthcare payers (such as insurance companies) use to decide whether to cover and reimburse a certain medical operation, prescription, or ser- vice. It entails getting the payer's consent before a healthcare service is rendered or a course of treatment is begun. Pre-authorization ensures that planned healthcare services or treatments satisfy the payer's requirements for coverage, which may include medical necessity, appropriateness, cost-effectiveness, and adherence to set standards or rules. It gives payers a mechanism to keep expenses under control, limit use, and guarantee that the services being rendered comply with the conditions of the insurance or healthcare plan.

Prior authorization is one healthcare procedure that GAI could potentially enhance. Even though the healthcare sector has made progress towards automating and standardizing PA, the procedure still presents administrative challenges. Reviewing PA requests requires a significant amount of clinical staff time from payers. According to reports, doctors and staff spend up to 13 hours each week on the PA process [41]; many clinicians think this compromises their clinical judgement and can delay providing timely care.

An in-depth evaluation by McKinsey and Company indicates that GAI-enabled Pre-Authorization can automate 50 to 75 per cent [41] of manual activities, increasing efficiency, lowering costs, and enabling clinicians at payers and providers to concentrate on challenging cases and actual care delivery and coordination. As a result, both clinicians and health insurance subscribers may have a better overall healthcare experience.

The current pre-authorization workflow involves much manual labour. Some payers have started the PA automation path to increase productivity, decrease provider distrust and unhappiness, and enhance doctor and client experiences. For instance, electronic prior authorization quickens the data flow between payers and providers. Electronic PA digitalizes workflows, which speeds up turnaround times. With electronic PA, close to 60 per cent of requests were fulfilled within two hours as opposed to zero requests sent by phone or fax.

The GAI may help organize data from electronic health records, emails, policies, medical procedures, and other sources by utilizing advanced Machine Learning algorithms like Natural Language Processing and digital and work- flow management technologies. This could significantly reduce low-value, time-consuming tasks involving searching, compiling, and validating details that people previously performed manually. While GAI will undoubtedly change the prior authorization process, several obstacles must first be solved. Payers will first want unrestricted access to EHRs, which requires rigorous adherence to data privacy laws and a significant amount of design work to assure interoperability among diverse EHR application software and platforms. Another crucial requirement for AI-driven PA automation is the definition of common criteria for attachments, data blueprints, and information-sharing protocols by industry participants at the operational level.

Although highly skilled physicians will always be the ones to make the final pre-authorization decisions, GAI can help payers and providers make critical decisions while also increasing efficiency and improving provider and patient experience. Insurance companies can delegate the most difficult and delicate decision-making to highly skilled doctors by automating most pre-authorization decisions. For optimal use of these advantages, stakeholders will need to collaborate to design a new set of standards for data sharing and additional protocols for system integration and interoperability.

K. MEDICAL TRIAGE

In medicine, triage is defined as prioritizing the care of patients (or catastrophe victims) based on their condition, severity, prognosis, and resource availability. Triage is used to identify patients requiring rapid resuscitation, allocate them to a designated patient care area to prioritize their care, and start necessary diagnostic and therapeutic procedures [42].

By offering helpful assistance and enhancing decision- making, generative AI has the potential to impact the field of medical triage significantly [43].Creating triage support systems is an important example of generative AI's use in medical triage. These systems analyze patient data, including symptoms, medical history, and test results, using deep learning and pattern recognition to provide predictions and suggestions on the criticality of therapy [44]. Generative AI can help healthcare personnel make better-educated triage decisions by quickly analyzing massive quantities of data.

Rapid triage can be made possible using the GAI in emergencies where time is of the essence. Disaster events and emergency departments sometimes include difficult circumstances and scarce resources. Healthcare practitioners can input patient information into the system using GAI models, which can quickly analyze the data and produce assessments that help prioritize patients based on the extent of their conditions. Assuring prompt care for individuals most in need can greatly improve productivity, the distribution of resources, and, ultimately, patient outcomes. Another field where GAI can help is in addressing inequalities in triage judgements. Implicit biases can have an impact on triage decisions, among other things. GAI can reduce these discrepancies by offering a data-driven, objective approach to triage. It is feasible to lessen prejudice and increase fairness in the triage process by training AI models on various representative datasets, ensuring that patients receive the proper degree of treatment based on their medical requirements rather than other criteria.

However, ethical issues are raised by using GAI in medical triage. To ensure that triage decisions can be understood, supported, and accepted by healthcare professionals and patients alike, transparency and explainability of AI models are essential. Furthermore, appropriate security measures must be implemented to defend patient privacy and guarantee the secure handling of sensitive medical data. It is imperative to understand that GAI should not take the role of human expertise. Cooperation between artificial intelligence systems and healthcare personnel is essential to properly integrate GAI into the triage process and take advantage of both parties' strengths Theriseo67:online. Recent developments in medical triage highlight the use of advanced AI, such as GAI tools, aiming to expedite decision-making by analyzing a wide range of patient information swiftly and accurately [45]. Furthermore, Predictive analytics models incorporating AI and machine learning are integrated into triage systems to forecast patient outcomes, predict disease progression, and identify high-risk patients. Medical triage can be greatly enhanced by combining the strength of generative AI with human judgement, improving patient care and utilization of resources in challenging healthcare scenarios.

L. TEXT GENERATION AND SUMMARIZATION

Medical data are abundant in medical records, scientific literature and patient feedback; extracting valuable information is time-consuming if done manually. GAI models like BART (Bidirectional and AutoRegressive Transformers) can provide significant support. BART is a transformer architecture that utilizes self-attention mechanisms to process and understand text data. By analyzing patient data and context, GAI models like BART can assist in generating clinical documentation such as discharge summaries, progress notes and medical reports that capture relevant information and generate personalized recommendations for diagnosis and treatment plans. BART reduces the burden on healthcare providers, allowing them to focus more on patient care; it can help generate patient-friendly explanations of medical conditions, treatment options and surgical procedures, thus filling any communication gap between patients and health- care providers.

BART can be leveraged for named entity recognition (NER). It can identify and classify specific entities within a text, such as names of people, medical terms or medications and aid in organizing and extracting relevant information from large volumes of text, thus enabling efficient retrieval of data points. Its ability to comprehend and generate coherent text aids in performing information extraction tasks. By analyzing patient data and using the information given, BART can produce accurate and standardized automated reports such as radiology, pathology, and laboratory reports. By leveraging GAI models' text generation and summa- rization capabilities, healthcare organizations can enhance communication, streamline documentation processes, and improve the accessibility and understanding of healthcare information. However, it is crucial to note that outputs generated by these models need to be validated by healthcare professionals to maintain accuracy, reliability, and adherence to ethical guidelines.

M. VIRTUAL REHABILITATION AND REHABILITATION ROBOTICS

For a long time, two communities of academics with differing pensiveness and interests have primarily researched genera- tive artificial intelligence and virtual environments. In virtual rehabilitation, where it may help create immersive and individualized patient experiences, generative AI has much potential. In order to create interesting and interactive settings for therapeutic reasons, virtual rehabilitation combines gen- erative models with virtual reality (VR) or augmented reality (AR) technologies. Because of this pairing, rehabilitation patients can have customized immersive experiences. For example, while movement replication models mimic and adjust patients' movements in virtual environments, pro- viding real-time feedback and encouraging motor control, gesture recognition models employ generative AI to enable patients to engage with virtual environments using natural hand movements. The GAI can also be applied to further develop and enhance rehabilitation robotics by generating adaptive robotic movements. The GAI examines patient features, mobility data, and treatment objectives to create customized rehabilitation plans. These programs allow robots to modify their movements, pressures, and levels of support in response to real-time feedback, maximizing patient par- ticipation and the efficiency of therapy. Patients can actively engage in the therapeutic process by using gestures that cause virtual responses and activities, opening up new paths for therapeutic interaction. Such interactive components improve the rehabilitation process and motivate patients, but they also help patients enhance their motor control abilities and give real-time feedback on their progression. By using the GAI in this field, healthcare professionals can facilitate better recovery outcomes for patients with medical impairments.

N. ADVERSE DRUG REACTION (ADR) PREDICTION

Adverse drug responses (ADRs) are unwanted and adverse effects of routine drug use. Enhancing drug safety and lowering costs can be achieved by anticipating and preventing ADRs early in drug development. According to a survey, over 2 million major adverse drug reactions (ADRs) are estimated to happen among hospitalized patients in the US each year, resulting in over 100,000 fatalities as a useful tool for anticipating adverse drug reactions (ADRs) during drug discovery and development.Generative methods can produce novel compounds with expected ADR profiles by examining vast datasets of drug structures, chemical characteristics, and known ADRs.

In addition to assisting in the early detection and prevention of adverse drug reactions (ADRs), GAI models provide insightful analyses into the intricate processes that underlie ADRs, fostering a deeper comprehension of drug safety. For instance, the BMC Bioinformatics journal published a neural fingerprint technique in a concurrent deep learning framework for ADR prediction such that the label infor- mation (drug-ADR relationship) can be used in the feature creation stage of the machine learning process. By creat- ing molecular explanations and emphasizing the pertinent chemical interactions, generative models can also help us understand the underlying mechanisms of the ADRs. The information on pharmaceuticals, ADRs, and target proteins may be better represented using knowledge graphs and GAI, which is extremely important for studying ADR prediction. Using GAI to study ADRs can completely transform drug discovery and development processes. We can build targeted therapies and interventions to reduce the impact of ADRs on patient outcomes as the field develops, and the synergy of GAI, deep learning, and knowledge graphs improves our understanding of ADR mechanisms.

O. SYNTHETIC NON-IMAGE DATA AUGMENTATION/GENERATION

Producing artificial or simulated data that closely mimics actual data is known as synthetic data production or augmentation. This method has grown in significance in the healthcare sector, especially in addressing data privacy issues, extending datasets, and improving the development and testing of algorithms. The GAI plays a crucial role in developing synthetic data by utilizing its capability to learn patterns and produce new data based on existing instances. Generative models can create artificial data points that capture the statistical traits and attributes of the original dataset by analyzing vast amounts of real patient data. This synthetic data can be utilized alongside current datasets, giving researchers and developers access to more varied data samples without sacrificing patient privacy. Additionally, controlled and repeatable datasets can be produced using synthetic data generation for benchmarking and algorithm evaluation.

The GAI can also generate synthetic data for specific use cases or scenarios that may be difficult to obtain or rare in real-world datasets. Techniques like GANs and VAEs have evolved to generate synthetic tabular data resembling original datasets, aiding in financial analysis, medical research, and structured data applications [46].This data can be used in areas with limited data availability and where generating more data is difficult or not feasible. Enhancing synthetic data with the GAI can also reduce the problems associated with imbalanced datasets. It is common in the healthcare sector to have skewed distributions of particular illnesses or demographic features due to several factors, such as data collection biases or the rarity of particular diseases. By creating synthetic data to balance these disparities, generic models can ensure that algorithms are trained on representative and diverse samples, leading to more accurate and equitable healthcare solutions. By effectively utilizing the power of the GAI for synthetic data augmentation, we can overcome the problem of data limitation and quicken the creation and implementation of AI-driven solutions for better patient outcomes and care.

P. BIOMARKER IDENTIFICATION

The process of finding and verifying particular biological markers that can be utilized as indicators of a particular disease, physiological condition, or response to treatment is known as biomarker identification. Biomarkers are quantifi- able traits that can reveal details about a biological condition. Examples include chemicals, genes, proteins, or imaging properties [47]. Biomarkers significantly impact disease diagnosis, prognosis, treatment choice, and monitoring in medicine and healthcare. Medical experts can learn more about a disease's presence, progression, and severity and assess the efficacy of treatment measures by identifying and measuring biomarkers [48].

The GAI offers a revolutionary method for identifying biomarkers in medicine and healthcare. Researchers may examine enormous and complex biological datasets to find new biomarkers by utilizing cutting-edge AI models like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs). The GAI augments conventional sta- tistical techniques, supplying a more thorough understanding of biological situations by revealing hidden patterns and linkages in genes, proteins, and imaging features. The GAI accelerates the detection of biomarkers by creating hypo- thetical biomarkers. The biomarker development process can be sped up, and expenses can be decreased by effectively testing and validating these AI-generated biomarkers in experimental settings. Additionally, by producing synthetic data, GAI assists in solving data shortages and privacy issues. In order to improve the robustness and reliability of biomarker detection, researchers can expand their datasets by creating synthetic samples that closely resemble real-world data.

The use of GAI in biomarker identification presents exciting possibilities for improving patient care and medical research. Artificial intelligence (AI) models speed up the identification of critical illness indicators and therapeutic responses by analyzing complex biological data and produc- ing fictitious biomarkers. This game-changing technology improves personalized therapy while deepening our under- standing of various illnesses, opening the door to precision medicine and better patient outcomes. In essence, while GAI's current role in biomarker identification might be in its infancy, it is untapped potential captivates researchers, promising groundbreaking strides in understanding biomark- ers' role in health and disease. As scientists explore and innovate at the intersection of GAI and biomarker identification, the prospects for revolutionizing diagnos- tics, prognostics, and personalized medicine are incredibly compelling.

Q. DISEASE PROGRESSION MODELING

In disease progression modelling, a disease's development, symptoms, and potential effects are examined and predicted through time. The GAI has the potential to be a powerful tool in this field and tremendously benefit the healthcare industry [49]. By analyzing huge databases of patient data, medical records, and clinical outcomes, generative models can discover patterns and linkages within the data and imitate disease development scenarios. These models can produce hypothetical patient trajectories that accurately depict the development of ailments while considering a variety of variables, such as genetics, lifestyle, and therapeutic inter- ventions. This makes it possible for medical practitioners and researchers to investigate multiple illness trajectories, assess the efficacy of different interventions, and appreciate the potential adverse consequences of different treatment modalities.

Liu et al. [50] introduce a novel end-to-end network designed to address the complexities of modeling diffuse gliomas, malignant brain tumors that extensively infiltrate brain tissue. The intricate interplay between neoplastic cells, normal tissue, and the changes induced by treatments presents challenges in accurately modeling glioma tumor growth. This approach is based on deep-segmentation neural networks and cutting-edge diffusion probabilistic models to generate future tumor masks and realistic MRIs depicting the anticipated tumor appearance at various future time points for diverse treatment plans. Sequential multi-parametric magnetic resonance images (MRI) and treatment information are used as conditioning inputs to guide the generative diffusion process, enabling tumor growth estimations at any specific time. By providing treatment-aware generated MRIs, tumour growth predictions, and uncertainty estimates, the model offers valuable insights for clinical decision-making, aiding clinicians in assessing potential outcomes and guiding treatment strategies.

Also, applying the GAI to progressing illnesses modeling can enhance clinical judgment, personalized healthcare, and our comprehension of diseases. In addition to reproducing disease trajectories, the GAI affects disease progression modelling. By employing vast amounts of healthcare data and clinical records, generative models can aid in predicting illness outcomes, evaluating the severity of the disease, and identifying high-risk patients. To present patients with cus- tomized risk profiles, these models can investigate complex correlations between various data, including the popula- tion, biomarkers, multiple medical conditions, and lifestyle choices. This enables medical professionals to make well- informed decisions about treatment plans and treatments, leading to more concentrated and effective healthcare prac- tices. Along with contributing to its predictive abilities, GAI can support the development of fresh perspectives and disease mechanism concepts. By examining the created disease progressions and their related characteristics, researchers can gain a deeper understanding of the fundamental mechanisms and processes that underlie the course of disease. This information can aid in creating fresh therapeutic targets, make it simpler to find prospective biomarkers and direct the investigation of novel therapeutic strategies. Moreover, the design and optimization of clinical trials may be improved using GAI. Researchers can examine alternative scenarios, evaluate the effectiveness of various interventions, and calculate the potential impact of new therapeutics by modelling illness development and treatment responses in virtual patient populations. This can speed up the discovery and approval of new treatments, lower expenses associated with the clinical trial process, and streamline the clinical trial process, eventually benefiting patients by giving them quicker access to cutting-edge therapies. The modeling of disease progression with the GAI has enormous potential. Tailored healthcare, better clinical decision-making, and a greater understanding of disease mechanisms all benefit from its capacity to analyze big datasets, simulate disease trajectories, and produce tailored risk profiles. By utilising the GAI, researchers and healthcare practitioners can improve treatment plans, understand disease progress, and boost healthcare delivery.

V. HEALTHCARE-CUSTOMIZED LARGE LANGUAGE MODELS

Advanced AI systems called large language models (LLMs) (GAI models) have been trained to understand and produce language in a way comparable to that of humans. These mod- els process and analyze text using deep learning techniques, enabling them to produce consistent and pertinent responses to the context. large language models offer the potential to improve human-computer interactions and automate jobs in numerous sectors where language understanding and generation are essential. In this section, we describe several GAI models that are customized for the healthcare domain.

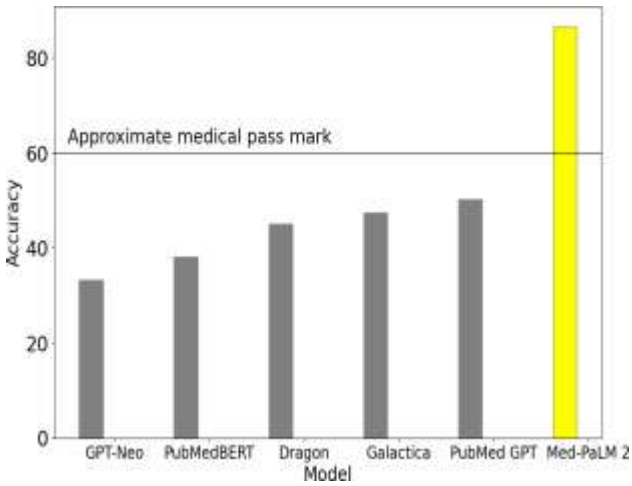

FIGURE 3. Performance of Med-PaLM over other healthcare LLM models.

A. *MED-PALM*

Med-PaLM [51] is a large language model (LLM) created to offer excellent responses to medical queries. It stands for Medical Pre-Trained Language Model.It is trained using extensive medical literature, academic publications, electronic health records, and other healthcare information. Med-PaLM has the capacity to comprehend medical jargon, decipher intricate medical ideas, and produce pertinent com- ments or insights [52]. In addition, Med-PaLM [53] produces precise, beneficial long-form responses to consumer health issues, as determined by panels of licensed doctors and users. Medical documentation, electronic health records, medical education and research, and information retrieval are only some of the applications that Med-PaLM can be used in the healthcare industry. Med-PaLM has the potential to improve efficiency, accuracy, and knowledge availability in numerous areas of healthcare delivery and research by making use of its extensive medical knowledge and language-generating capabilities. Recently, Google launched an upgraded model of Med-PaLM called Med-PaLM 2 [54], which has an 18% leap in accuracy compared to its predecessor. Med-PaLM 2 achieved a staggering 86.5% accuracy rate on the United States Medical Licensing Examination (USMLE) questions [52], which is on par with the ‘‘expert’’ test takers. Figure3 shows the perfor- mance of Med-Palm over other medical models. Med-Palm 2 could surpass the 60% passing threshold required for the examination.

Med-PaLM has several key capabilities that make it valu- able in the medical sector. For instance, Med-PaLM aids in the representation of medical knowledge. Anatomy, illnesses, symptoms, treatments, drugs, and medical procedures are all included in the Med-PaLM encoding system for medical knowledge. Because of this expertise, the model can interpret and produce text unique to medical themes. By doing so, Med-PaLM plays a vital role in representing medical knowledge. The area of medical documentation is another one where Med-PaLM is widely employed. Med-PaLM aids in producing thorough and accurate medical records. It can construct reports, automatically extract pertinent data from patient contacts, and help keep standardized terminology in electronic health records (EHRs). Figure 4 shows the diagnostic report generated by Med-Palm 2 by analyzing the image of a chest X-ray [55].

Additionally, Med-PaLM is useful in medical research and education. Medical students, researchers, and instructors can use the model's extensive medical knowledge base and language-generating skills. To help in studying and comprehending difficult medical ideas, Med-PaLM can offer definitions, justifications, and responses to medical questions.Condensing research papers, highlighting pertinent information, and extracting essential conclusions can help with literature reviews. Med-PaLM may also create hypothe- ses, recommend research topics, and promote evidence- based practice by giving users access to the most recent medical literature. Information retrieval in the medical industry may benefit from the use of Med-PaLM. It can efficiently search for and retrieve pertinent research articles, guidelines, clinical trials, and other sources of medical knowledge because of its capacity to process and comprehend medical content; This enables medical practitioners to obtain the most recent, scientifically supported information, fostering informed decision-making and improving patient care.

Despite the fact that Med-PaLM 2 achieved state-of- the-art performance on several multiple-choice benchmarks for medical question answering and that human evaluation shows answers compare favourably to physician answers across several clinically important axes, more work needs to be done to ensure it is used safely and effectively.The ethical application of this technology will require careful thought, including thorough quality assessment when utilized in various clinical contexts with safeguards to reduce hazards in such circumstances. For instance, utilizing an LLM to determine a patient's diagnosis or course of treatment carries significantly more risks than using an LLM to learn about a condition or drug. More research is required to evaluate LLMs used in healthcare for homogeneity and amplification of biases and security vulnerabilities inherited from base models. Another drawback is the potential for Med-PaLM to produce plausible yet inaccurate or deceptive information. Sometimes language models can produce responses that appear sensible but lack medical precision or evidence- based backing. Healthcare practitioners should use prudence and cross-reference the data supplied by Med-PaLM with reliable sources and their own experience. Additionally, Med- PaLM can have trouble handling sensitive patient data and upholding privacy. When adopting Med-PaLM or any other language model, appropriate safeguards must be in place to secure sensitive information because patient privacy and data security are crucial considerations in the healthcare industry.

B. BIOGPT

BioGPT [56] is a pre-trained transformer language model that is domain-specifically generative and designed for producing and mining biomedical texts. BioGPT is pre-trained on 15M PubMed abstracts from scratch and adheres to the transformer language model framework (GPT-2). BioGPT is capable of carrying out tasks like providing information, retrieving relevant information, and producing writing pertinent to biomedical literature. The goal of BioGPT, which emphasizes the biomedical field, is to help researchers, medical personnel, and scientists with various tasks, such as literature reviews, drug discovery, protein modelling, and biomedical data analysis.

In comparison to a single human annotation, BioGPT- Large scored a record 81% accuracy on PubMedQA. The accuracy of most other NLP tools, including Google's BERT family of language models, has not surpassed that of humans. BioGPT has several use cases in the field of bio-medicine and bio-informatics. Personalized medicine, drug discovery, protein modelling, bio-informatics analysis, literature review, and educational help in the biomedical and bioinformatics disciplines are some of the applications of BioGPT. It can contribute to different facets of scientific research, medical care, and educational endeavours in these fields because of its capacity to comprehend and produce human-like language in the setting of biology. By quickly finding appropriate information from voluminous biomedical literature, BioGPT can support literature reviews and research. Researchers can use the approach to summarize study articles, extract essential findings, and detect relationships between various studies; This helps scholars stay current with the most recent developments in their fields while saving time. Additionally, BioGPT can support bioinformatics studies and protein modelling. It can help with domain identification, protein-protein interactions, and protein structure prediction. BioGPT may provide researchers with thorough knowledge of genes, pathways, and biological networks by integrating diverse biological databases and knowledge sources, which can help with data interpretation and analysis.

BioGPT presents several of the same challenges as Chat-GPT despite being trained primarily in biomedical literature. Inaccurate writing without any references produced by generative language models is of growing concern because it may spread false information. Additionally, because BioGPT is trained using previously published medical studies that may contain biases, there is a chance that the GAI will reinforce those prejudices. The model's ability to produce consistent and human-like responses raises questions about possible abuse or the spread of false information. The thorough mon-itoring, validation, and implementation of suitable controls to avoid spreading false or biased information are necessary for the responsible and ethical deployment of BioGPT. While BioGPT might be useful in decision-making and biological research, it should not replace the experience and wisdom of researchers or healthcare professionals. The model's outputs should be used to support human judgment rather than as a replace[...]tise, and expert opinion.

C. IBM WATSON FOR ONCOLOGY

The GAI-powered IBM Watson for Oncology system [57] was created to aid oncologists in selecting the best course of treatment for cancer patients. It analyzes a large amount of medical literature, patient data, and therapy recommendations using natural language processing, machine learning, and big data analytics methods [58]. Watson for Oncology aids oncologists in quickly accessing pertinent medical informa- tion by processing and comprehending unstructured clinical material. It also offers recommendations for treatments that are supported by evidence.

Oncologists typically use Watson for Oncology as a deci- sion support tool in the healthcare sector. It can be connected with electronic health records (EHRs) and other data to analyze patient data, including medical history, test results, pathology reports, and treatment recommendations, sources [58]. The system evaluates patient information against a sizable knowledge collection that includes academic papers, clinical studies, treatment regimens, and medical textbooks. Then, tailored to each patient's particular characteristics, oncologists can receive recommendations and insights on prospective therapy alternatives. The availability of expert knowledge is one of IBM Watson for Oncology's main advan- tages [57]. Oncologists can access a lot of clinical information and medical literature through the system, which may be difficult to keep up with manually. It provides oncologists with evidence-based treatment options by providing them with access to the most up-to-date research and clinical recommendations.

A significant additional benefit is the tailored thera- peutic recommendations offered by Watson for Oncology. The algorithm considers patient-specific characteristics like health history, genetic data, and treatment response to create personalized therapeutic options. As a result, oncologists can tailor treatment plans for specific individuals, consider- ing their particular needs and circumstances. Additionally, Watson for Oncology has advantages for time management [57]. Oncologists can save a great deal of time by using technology to quickly assess huge volumes of patient data and medical literature. Oncologists can review and make wise decisions more quickly since it concisely delivers synthesized and pertinent information.

It is important to remember that IBM Watson for Oncology has some restrictions. The lack of adequate clinical validation is one drawback. Despite being educated on a vast body of medical research, Watson for Oncology's suggestions could not always coincide with those of particular oncologists or established institutional policies. The system's suggestions need extensive clinical confirmation and be viewed as an additional tool to aid clinical judgment rather than as a complete answer [58]. While Watson for Oncology excels

FIGURE 4. X-ray report analysis as done by Med-PaLM 2.

at evaluating vast amounts of data, it might have trouble deciphering difficult or uncommon instances when there is a lack of data. It heavily relies on the availability of pertinent medical literature and clinical evidence to create recommendations, which may be scarcer for particular cancer kinds or patient populations.

In a broader sense, IBM Watson for Oncology is an AI-driven system that supports oncologists in treatment decision-making by offering recommendations supported by patient data and medical expertise.Personalized treatment options and access to various information are provided, but its recommendations should be carefully weighed, and its incorporation into clinical processes should be rigorously assessed.

D. HEALTHCARE LANGUAGE MODELS BY NVIDIA CLARA

The NVIDIA Clara platform is a collection of AI-powered tools and frameworks created primarily for healthcare applications [59]. Healthcare language models trained to comprehend and interpret content written in medical natural language are part of the Clara ecosystem [60]. These models are essential for facilitating efficient clinical natural language processing (NLP) tasks and assisting healthcare professionals in making decisions. The substantial medical text data used to train the NVIDIA Clara healthcare language models includes electronic health records (EHRs), medical literature, clinical guidelines, and other medical sources. The models can understand the complex language patterns, medical terminologies, and context unique to the healthcare sector by utilizing this enormous corpus of medical material [59]. The deep learning architectures used to create these language models, including transformer-based models, have proven incredibly effective at various tasks involving natural language processing. Clinical entity recognition, medical concept normalization, relation extraction, and clinical text categorization are just a few of the NLP tasks the models are taught to handle specifically for the healthcare industry [60]. Numerous healthcare applications can make use of NVIDIA Clara's healthcare language models. They can be used, for instance, to automatically extract and categorize clinical entities from unstructured clinical literature, such as identifying diagnoses, drugs, procedures, and test find- ings. This skill is useful for clinical decision assistance, clinical documentation improvement, and automated medical coding. The models could potentially improve efforts in tailored medication. The models can identify significant traits and trends supporting tailored treatment choices by reading, interpreting, and comprehending clinical narratives distinct to individual patients; This can help with treat- ment choice, forecasting treatment results, and facilitating precision medicine techniques. Overall, NVIDIA Clara's healthcare language models give the healthcare industry access to the power of cutting-edge NLP [60]. These models provide insightful information, boost productivity, and help clinical decision-making for various healthcare applications by comprehending and processing medical text data.

E. DEEPHEALTH LLM

MIT and Massachusetts General Hospital researchers created the extensive language model known as DeepHealth [61]. It makes use of machine learning and natural language processing to meet the specific possibilities and challenges faced by the healthcare sector. DeepHealth attempts to close the knowledge gap between unstructured clinical data and insights that healthcare professionals may use. DeepHealth is employed in the healthcare sector to improve many facets of healthcare delivery and decision-making [62]. Answering clinical questions is a crucial application. In order to deliver accurate and contextually appropriate answers to certain clinical issues posed by healthcare professionals, the model may assess medical material, such as research articles and clinical recommendations; This can speed up knowledge retrieval and aid in the use of evidence when making decisions. Medical image analysis is another field in which DeepHealth can be applied. The model has been trained to comprehend radiology reports and medical images, allowing it to draw out important details and help with complex image interpretation. It can help with disease diagnosis, abnormality detection, and insight into treatment planning [63].

By examining patient-specific clinical narratives, Deep- Health aids in the advancement of personalized medicine initiatives. The program can process and comprehend each unique patient's medical records to extract patterns, risk factors, and treatment outcomes that help determine the best course of therapy; This can help with treatment outcome prediction and precision medicine strategy guidance.

However, DeepHealth has several limitations, much like any noteworthy language model. The requirement for con- siderable training data and the potential for biases in the training data are two major limitations. The calibre and variety of the data used to train the model significantly impact its performance. The predictions and suggestions made by the model could potentially be affected by biases in the data. Furthermore, it is difficult to interpret the model's predictions. Even though DeepHealth can offer viewpoints and suggestions, it can be difficult to comprehend the underlying logic or describe the decision-making process. Concerns may be raised by this lack of interpretability in complex medical situations where explainability is essential. To summarize, DeepHealth is a large language model created especially for healthcare applications. In order to improve clinical question answering, medical picture analy- sis, and personalized treatment, it uses machine learning and natural language processing techniques [62]. Benefits include faster access to medical information, time savings, and encouragement of evidence-based decision-making. How- ever, difficulties with interpretability, domain adaptation, and the quality of the training data persist, which call for careful consideration when using the model in various healthcare contexts.

F. BIOBERT

Developed primarily for biomedical text mining and natural language processing (NLP) activities in the healthcare sector, BioBERT (Bidirectional Encoder Representations from Transformers for Biomedical Text Mining) is a large language model. It has been trained on a sizable corpus of biological literature and is based on the BERT architecture (Bidirectional Encoder Representations from Transformers) [64]. BioBERT has shown to be a useful tool for sifting through biomedical literature and supporting various health- care applications. BioBERT is frequently used in healthcare for tasks like text classification, relation extraction, question answering, and biomedical named entity recognition. It is extremely good at processing clinical and scientific materials because it can comprehend the language and vocabulary unique to the biomedical area. BioBERT can recognize and extract biomedical items from unstructured text data, including diseases, genes, proteins, chemicals, and their interactions [64]. Figure 5 shows how the pre-training and fine-tuning of large language models like BioBert is done with the help of the vast medical corpora.

Enhancing the effectiveness and precision of biomedical information extraction is one of BioBERT's key advantages. BioBERT can comprehend the subtleties and intricate linkages found in biomedical texts by using the contextual knowledge and semantic representation developed during training; This helps with activities like automatic annotation,

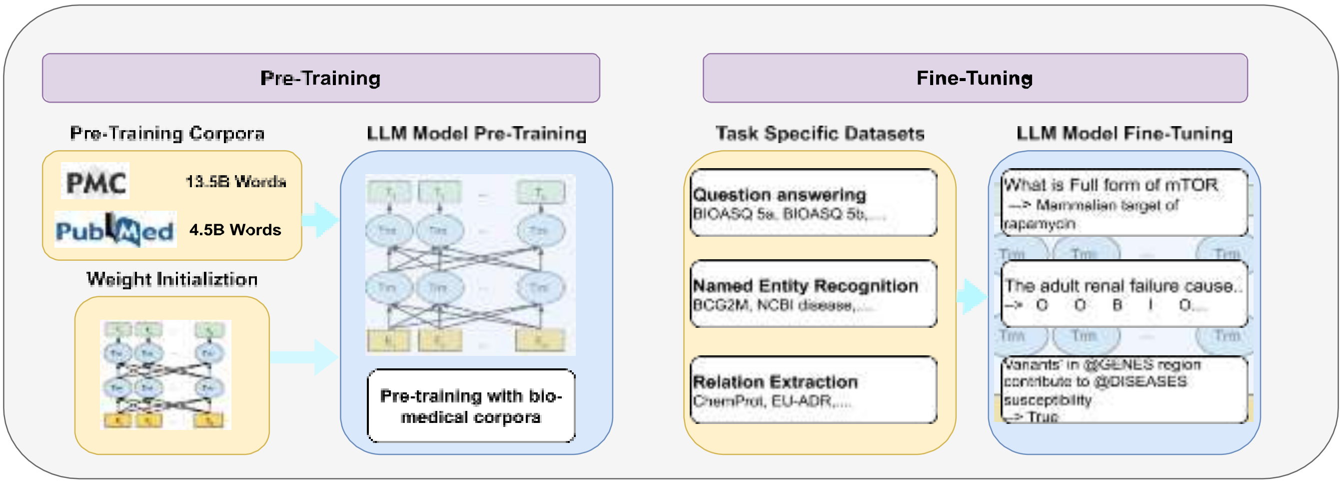

FIGURE 5. Pre-Training and fine-tuning of large language models.

database curation, and the extraction of insightful information from research publications [64]. Support for biomedical research and evidence-based medicine is another benefit of BioBERT. The model can help with literature reviews, knowledge discovery, and hypothesis development by look- ing at a lot of biomedical literature. It gives researchers and healthcare practitioners access to a vast knowledge base, facilitating decision-making, study design, and the advancement of scientific knowledge. BioBERT can also fill the divide between structured and unstructured clinical data. BioBERT enriches electronic health records (EHRs) and facilitates a more thorough study of patient data by removing pertinent biological elements and their relationships from clinical narratives [64]. Patient stratification, clinical decision support systems, and population health analytics can all benefit from this.

However, BioBERT also has certain drawbacks. The availability and calibre of training data constitute one restriction. Despite being trained in a vast body of biological literature, BioBERT may not comprehensively understand some fields or rare ailments; This may impact its performance on specialized or understudied issues. Furthermore, biases in the training data may affect the model's output and cause unexpected biases in applications used afterwards. Additionally, the computing demands of BioBERT and resource-intensive nature can make it difficult to implement it on edge devices or in environments with limited resources. The model's size and processing requirements might make it less accessible and useful in some healthcare applications.

In a nutshell, BioBERT is a potent language model created for NLP and biomedical text-mining jobs in the healthcare sector. Improved information extraction efficiency, support for research and medicine based on evidence, and enrichment of clinical data are some of its advantages [64]. However, while applying BioBERT in healthcare applications, it is important to take into account its limitations, which include data accessibility and quality, interpretability, and computing needs.

G. *MED7 LLM*

A large language model called Med7 was created especially for medical NLU (natural language understanding) in the healthcare sector. Med7 is a clinical text data extraction tool trained on a wide variety of clinical text data [65]. Unstructured clinical text sources include electronic health records (EHRs), clinical notes, and medical literature. It focuses on identifying medical entities and their corresponding qualities to make clinical data analysis more effective and reliable. Med7 is employed in the healthcare sector to simplify several processes involving extracting clinical information. It can automatically identify and extract medical elements such as diseases, symptoms, medications, therapies, and test results from unstructured clinical data. Med7 helps to enhance clinical documentation, improve clinical coding, and promote clinical decision-making by converting free-text clinical narratives into structured data [65]. One of Med7's key advantages is its better accuracy and efficiency when processing and understanding clinical language. Applying the knowledge and context it acquired throughout training has allowed Med7 to identify medical organizations and their properties accurately; This improves healthcare information's accuracy and thoroughness while requiring less manual labour to separate organized data from unorganized clinical information.

Additionally, Med7 enhances the interoperability and data integration of healthcare systems. Med7 enables data sharing, communication, and analysis amongst various healthcare platforms by transforming unstructured clinical language into structured data [65]; This makes it possible for electronic health record (EHR) systems, decision support tools, and other healthcare systems to integrate seamlessly, thereby increasing patient continuity and data interoperability. The potential for Med7 to help clinical research and community health investigations is an additional advantage. Med7 supports cohort identification, patient stratification, and data analysis for research by effectively extracting medical entities and their features from clinical narratives. It makes large- scale data mining and analytics possible by enhancing both medical research and evidence-based medicine [65].

However, Med7 also has certain limitations that must be taken into account. Its reliance on the calibre and variety of the training data is one of its limitations. The availability and representativeness of the clinical literature that the model is trained on can have an impact on how well it performs. The accuracy and generalizability of the model's predictions can be affected by biases or gaps in the training data. Additionally, Med7 acts as a ''black box,'' which can restrict interpretability, like other big language models. Comprehending the underlying theory or explanation underlying the model's predictions can be difficult. In crucial healthcare situations where explainability is crucial, this lack of interpretability may cause problems. For proper use of Med7 in healthcare applications, it is essential to be aware of these constraints.

VI. REAL WORLD PERFORMANCE ASSESSMENT OF GAI IN HEALTHCARE

Using innovative solutions to overcome traditional methods is essential in healthcare. The use of GAI has been progressively increasing in various fields. This section will discuss four real-world use cases where the GAI has played an essential role in healthcare.

A. *VISUAL SNOW SYNDROME*

A positive visual disturbance known as visual snow syn- drome (VSS) [66] has been characterized as the persistent flickering of countless tiny dots throughout the visual field. Alternatively, it is similar to viewing the world through the static noise of an improperly tuned television. The condition requires innovative approaches for understanding and man- aging, as its subjective nature and diverse symptomatology make it challenging to diagnose traditionally. The current diagnostic criteria for visual snow syndrome include the presence of minute dots throughout the entire visual field lasting longer than three months, as well as the presence of at least two of the visual symptoms listed below: photophobia, nyctalopia, palinopsia, and entoptic phenomena.

Visual snow is a reasonably uncommon syndrome expe- rienced worldwide, and as the researchers' understanding evolves, exploring new innovative technologies becomes crucial for further understanding and advancement, analysis, and improving patient care for people suffering from this perplexing chronic disease. The diagnosis is primarily based on patients' verbal descriptions of their symptoms; this causes a barrier to understanding the true nature of the disease, as individual patients may describe their experience differently, which may be difficult for parents and other healthcare members. For better understanding and seeing

FIGURE 6. Generation of an image using stable diffusion with the text prompt ''seeing a playground through grainy static interface''.

through the eyes of the patients, Balas and Micieli [67] made use of GAI technologies to generate images of how a patient affected with visual snow syndrome sees with the help of textual descriptions with the help of generative artificial intelligence models that could translate text to the image. Various models were used to get a clear image, such as DALL·E2 [2], midjourney [3] and stable diffusion [4]. Figure 6 shows an image generated by Stable diffusion with the text prompt "seeing a playground through grainy static interface". Although the current situation of generative text-to-image models shows promising results, more research and training must be done to achieve precise results that can be directly used in the medical industry.

B. *MOLECULAR OPTIMIZATION*

Molecular optimization is the process of improving the properties and characteristics of chemical compounds which can alter the activity of the target molecule in a desired way. Finding the perfect molecule for a set of specific requirements organically is very difficult, and designing a molecule from scratch with all the rightful properties is a challenging and complex task requiring a lot of time and resources as these molecular structures have complex properties. Furthermore, traditional molecule development methods are costly; 2005 pharmaceutical companies spent $2.6 billion to develop new US Food and Drug Administration-approved drugs [68]. With the growth in computational power and the development of new tools, it is essential to utilize advanced AI tools to optimize drug discovery. Deep generative models are becoming popular and can automate the generation of new bioactive and synthesizable molecules.

Molecular optimization can be helped with the help of generative AI.Molecular Optimization with GAI(MOGA) evaluates many molecular structures using GAI models. Mol-CycleGAN [69], a CycleGAN-based model, is a generative model which improves the compound designing process. At its core, it has two neural networks: a generator and

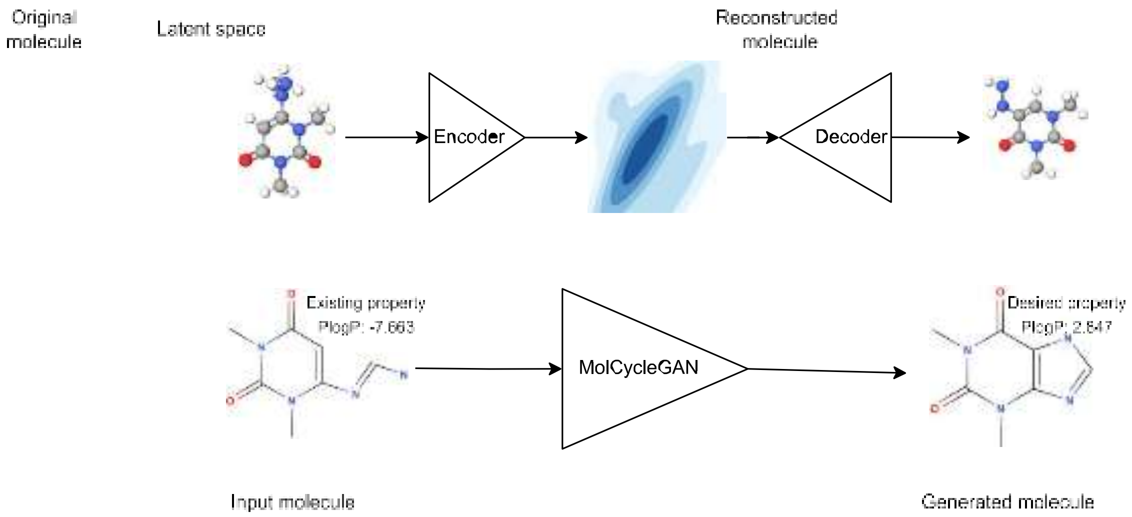

FIGURE 7. GAI models for molecular optimization.

a discriminator. The generator network learns to generate realistic molecular structures, whereas the discriminator network tries to distinguish between generated and actual molecules. Maziarka et al. [69]. Discuss how Mol-CycleGAN can generate a similarly structured molecule with optimized parameter values. The model was evaluated on optimization objectives based on structural and physicochemical proper- ties. Octanol-water partition coefficient (logP) penalized was used to test molecular optimization. The model was able to increase the activity of a specific inactive drug.
CADD is Computer Aided Drug Design, which uses in silico methods to leverage existing chemical knowl- edge. De novo design and virtual screening are two main approaches for drug designing; de novo design uses generative AI models and has seen rapid progress [70]. Mol- CycleGAN is used to generate novel molecules which have multiparameter optimization. It leverages image-to-image translation to transform molecular structures between differ- ent representations or chemical spaces, optimizing desired properties. The model trains from molecules from different chemical spaces named source space and target space and can map the two spaces without requiring a direct correspondence between specific molecules and generate molecules in the target space with desirable properties. Once the model is trained, it can be used directly for molecular optimizationby providing the molecular structure from the source space and defining details from the target space; the model generated has the desired structure and properties. Figure 7 displays the generation of the new molecule using GAI models Variational Autoencoder and MolCycleGAN; the generated molecules have a similar structure to the original molecule but with optimized penalized logP value [69]. As Mol-CycleGAN preserves structural details, it can maintain cycle consistency; that is, the generated molecules can be converted back to their original space while conserving their essential features.
It allows the generated molecules to be refined and improved via iterative optimization loops.
In their study, Grisoni et al. [71] employed a combination of generative deep learning models and a microfluidic platform to achieve a combination of generative AI and on-chip chemical synthesis and successfully generated liver
X receptor (LXR) agonists. Their research focused on generating novel molecular compounds using a specifically tuned computational pipeline that explored the chemical space of LXR-alpha agonists. The pipeline was limited to products derived from 17 one-step reactions to ensure compatibility with on-chip synthesis. The GAI model used in the study produced 25 de novo designs, which underwent subsequent retesting, batch resynthesis and purification. Out of the 14 retested designs, 12 were confirmed to be potent LXR agonists. This design-make-test-analyze framework demonstrated its suitability for drug design purposes. It show- cased the potential of combining generative deep-learning models with microfluidic platforms for efficient and effective chemical synthesis.
Bagal et al. [72] leverage deep learning techniques, particularly transformer-based models, for de novo molecule generation, known as inverse molecular design. This design utilizes SMILES notation to represent character strings, enabling natural language processing models for molecular design. This approach utilizes generative pre-training (GPT) models to train a transformer-decoder using masked self-attention for predicting the next token, focusing on generating druglike molecules. The MolGPT model performs similarly to modern machine learning frameworks in generating valid, unique, and novel molecules.
GAI models offer their unique ability to generate desired compounds. This approach allows researchers to navigate the vast chemical landscape and uncover new compounds which exhibit many properties, including improved efficacy,

reduced toxicity, enhanced stability, or other desirable characteristics. Utilizing a generative model for molecule synthesis saves time and resources by automating the optimization process and facilitating the generation of diverse and high- quality molecular structures.

C. MEDICAL EDUCATION

Generative language models (GLMs) and artificial intel- ligence (AI) can enhance medical education in various ways, such as through virtual patients, accurate simulations, customized feedback, evaluation techniques, and eliminating linguistic obstacles. These innovative tools can enhance med- ical students' educational outcomes and facilitate immersive learning environments [73]. Interaction between educators, researchers, and practitioners is essential to developing healthy practices, regulations, and transparent AI models that support the moral and responsible use of GLMs and AI in medical education. Developers can gain greater confidence and respect from the medical community by being open and transparent about the data utilized for training, challenges faced, and evaluation techniques.
Medical education has the potential to be transformed by contemporary GAI models with enhanced effectiveness, interactivity, and authenticity, such as OpenAI's ChatGPT and Google's BARD [74]. These models provide unprece- dented capabilities, including producing text that sounds like people, simulating difficult patient scenarios, and delivering customized learning experiences [75]; This encourages the creation of a more interesting and relevant learning environment. These GAI tools offer a more dynamic and realistic learning experience than conventional computer- based simulations. They provide more complex practice settings for medical students, facilitating clinical judgment and patient care. By utilizing GLMs' superior natural lan- guage understanding and producing capabilities, platforms like PerSim [76], a novel method of delivering medical simulation, provide students with contextually relevant patient situations that are more dynamic and adaptive than earlier computer-based models. During simulation exercises, these AI systems can offer real-time, personalized feedback based on a learner's performance and particular learning needs. Students who receive this evaluation can discover their strengths and areas for development.
With the use of GAI in formative and summative assess- ments, medical education can gain from more individualized, efficient, and targeted evaluation methods [77]. An example of the application of GAI in medical education assessments is the generation of customized quizzes for students. A unique formative and summative examination can be created for each student by GAI once their strengths and limitations have been examined. By analyzing student performance and giving real-time feedback, these artificial intelligence- driven solutions can assist instructors in creating personalized learning programs that cater to individual requirements and enhance overall results. GLMs can be used by a medical educator to create a variety of simulated patient scenarios. Students can become familiar with a wide range of medical issues and patient interactions because of the variety and realism of these scenarios. For instance, a medical student could converse with a dummy patient simulating a rare disease, ask questions, and get answers like actual patients. This can allow the learner to enhance their clinical reasoning abilities in a secure setting.
The proficient ability of these models to produce text with various levels of complexity could improve the availability of medical information. AI tools can potentially improve the accessibility and comprehension of health information for a wide variety of people, from non-specialists to medical professionals, by changing the language and terminology used according to the intended audience. This targeted communication strategy can increase health literacy and enable people to make better decisions about their health. By producing more explanations, examples, and visual aids, language models like chatGPT can improve medical textbooks. Students' general comprehension of the subject matter can be improved by making difficult medical ideas more understandable. Also, medical students will find it smoother to readily understand a study's main conclusions and consequences if language models like chatGPT are trained to summarize medical research publications. This can assist students in staying current with the most recent research in their subject while saving them time.
While there are numerous current and future potential benefits of using GAI in the medical education sector, they are not without a few limitations. Potential problems with precision, dependability, abuse of AI-generated content, and worries about academic integrity are real and warrant serious consideration. The possibility of bias, privacy concerns, and potential dehumanization in the educational process also warrant caution. The ''digital divide'' is a further crucial factor to consider. Unfair access to AI resources and technology could worsen existing inequalities in the educational system, especially in low-resource environments and among disadvantaged student groups. In our age, cyberattacks and the possibility of spreading misinformation are two major worries that come with AI integration into the medical education sector.
The medical education area must be particularly watchful and aggressive in handling these possible issues, given the high stakes in health care and the potential for harm. So, for example, the AI-generated material must be of the highest calibre. It needs to be carefully evaluated to make sure it is accurate and pertinent. Comprehensive and detailed feedback loops and appropriate prompting are two strategies that can help improve the accuracy and dependability of AI-generated content in medical education. AI systems have been seen to engage in biased behaviour and further enlarge pre-existing stereotypes due to their training data and occasionally due to the skewed dataset. Exercise caution and overcome any biases when implementing GLMs in medical education. Numerous earlier examples, such as racial biases in facial recognition

software and Chatbot Tay [78] from Microsoft tweeting offensive and sexist content, highlight the need for caution. In addition, ethical and legal concerns are raised by the use of generative AI in medical education, emphasizing the necessity for students to get AI ethics training to ensure the responsible and ethical implementation of these cutting-edge technologies.

In conclusion, both potential and challenges come with integrating GLMs and AI into medical education. GAI models can produce precise, individualized content for pupils, resulting in more productive learning occasions.It is imperative to properly heed potential biases and ethical problems to implement these cutting-edge technologies. These models' algorithms rely on enormous amounts of data, and if that data reflects systemic disparities or is biased, it could perpetuate unequal learning opportunities or strengthen pre-existing stereotypes. Certain controls and validation procedures must be implemented to ensure justice, equity, and inclusivity in the instructional content produced by GAI models. Educators, researchers, and practitioners must work together to develop standards, regulations, and best practices that support the moral and efficient integration of GAI models in medical education. Building trust and credibility in AI-powered medical education is largely a function of transparency. Those who developed and implemented these technologies must openly disclose the underlying algorithms, data sources, and procedures used in creating educational content. This openness promotes a better awareness of the constraints, prejudices, and potential uncertainties related to AI models, enabling educators and students to assess the offered instructional content critically.

D. DENTISTRY

Dental treatment could be enhanced by GAI, which has the potential to transform the medical field [79]. Dental research can help to make sure AI is utilized to improve dental treatment, make it more accessible, and benefit patients, practitioners, and society at large. The introduction of AI in dentistry is revolutionizing the industry by enabling higher precision, fewer mistakes, and reduced human resources needs. By using contemporary dental technologies like medical robots and specialized AI models, a new age known as dentistry might greatly increase dentistry's relia- bility, reproducibility, precision, and efficiency. Additionally, Dentronics might improve risk-assessment techniques, diag- nostics, and disease prediction in addition to improving treatment outcomes by deepening our understanding of disease pathophysiology.

By examining patient information like CT scans or 3D models of the mouth and creating the most effective implant placement plans, GAI models can also help with dental implant planning.To create individualized treatment plans for each patient, these models may simulate various scenarios while considering elements like bone density, nearby teeth, and functional requirements. Similar to this example, these GAI models can provide digital photos or 3D models of potential smile alterations by evaluating facial characteristics, tooth shape, and proportions. Then, dentists can create customized and realistic smile designs for people seeking cosmetic dentistry procedures. They can interact with patients and ensure their needs are properly handled. In order to identify and categorize different oral disorders, such as cavities, periodontal diseases, and oral malignancies, GAI models can be trained to analyze photographs or scans of the mouth cavity. These models can help dentists make early diagnoses and detections, improving patient outcomes. Dental clinical applications and research have a great deal of potential to be improved by modern language models like ChatGPT. They can revolutionize dentistry diagnostics and treatment planning [80].

While GAI models can help in the dental industry, they should be used to assist dental practitioners rather than taking the place of practitioners themselves. GAI models should be viewed as instruments to improve dentists' talents and the care they provide for patients because they play a crucial part in diagnosing and treating oral disorders. Using generative AI in the dentistry sector comes with limitations as well. The training data's precision and variety significantly impact the correctness and dependability of these models. Therefore, having incomplete or biased data can result in less-than-ideal outcomes and could also result in errors in diagnosis or treatment planning. The entire clinical context and patient-specific aspects, such as medical history, lifestyle, or individual variances, which are critical in dental care, are not considered by generative AI models. Complex decision-making in dentistry requires human expertise and judgment, which AI models cannot fully mimic.

Also, GAI models generally look for patterns and gener- alizations in training data but could miss important patient-specific elements. Important factors like medical history, lifestyle decisions, dental hygiene practices, and individual differences are not usually properly considered. Because of this, the produced outputs might not exactly match a patient's particular situation, which could result in less- than-ideal treatment plans or recommendations.Furthermore, GAI models' poor interpretability and transparency present a problem. It becomes more challenging to comprehend the underlying decision-making process, which limits dentists' and patients' capacity to fully trust and comprehend the created outputs. To make informed decisions and guarantee the safety of their patients, dental professionals need clear explanations and clarity about how the AI arrived at its conclusions.

VII. LIMITATIONS OF USING GAI IN HEALTHCARE

The GAI shows great promise in the healthcare industry; it offers an innovative approach towards traditional methods and has various advantages. Table 2 shows a list of types of content forms for which large language models (LLMs) are available now and possible models which can be available in the future [18]. However, it is vital to note that GAI has various limitations, like data bias and ethical considerations. Understanding these limitations is crucial for advancing this technology in the healthcare sector. Figure 8 displays the limitations and possible future works that can be implemented while integrating generative AI in healthcare.

1) ATTRIBUTION PROBLEM

The difficulty of comprehending and elucidating the motivations behind the judgements or outputs produced by GAI models in healthcare applications is known as the ‘‘attribution problem’’ connected with its usage [81]. Deep learning models, one type of GAI, have demonstrated an extraordinary ability to produce complicated and realistic data, such as patient records, medical images, and therapy recommen- dations. These models frequently cannot be understood or explained easily, preventing their responsible and efficient application in healthcare settings. Because GAI models function as complicated black boxes, it is challenging to identify and credit the decision-making process. This poses an attribution problem. It is more difficult to comprehend how and why a GAI model arrived at a specific output than conventional rule-based systems or simpler machine learning models. In the healthcare industry, this lack of transparency presents many difficulties. GAI models may unintentionally inherit biases or unequal representation of specific populations when trained on huge datasets. Finding and correcting biases in the generated outputs is difficult without adequate attribution. This can exacerbate already- existing inequities and result in differences in healthcare outcomes. Comprehending the attribution and potential biases in GAI models is crucial to ensure just and equitable healthcare delivery [81].

The attribution issue also presents ethical and legal issues. It is essential in the healthcare industry to be able to assign blame and accountability for choices made. It might be challenging to pinpoint who or what is at fault if a GAI model generates inaccurate or harmful results. This lack of accountability on a legal and moral level brings concerns about liability and patient safety. Healthcare organizations and providers can be reluctant to employ GAI solutions without clear attribution mechanisms. The attribution issue in GAI is currently being worked upon. Attention mechanisms, saliency maps, and post-hoc analysis approaches are just a few of the methodologies being researched for interpretability and comprehensibility. These strategies hope to shed light on the model’s decision-making process by tying the outputs to particular features or inputs. Healthcare practitioners can more accurately evaluate generative AI models’ biases, limitations, and dependability by comprehending the attribution, ensuring their responsible and efficient usage in healthcare.

2) CONTEXTUALIZATION PROBLEM

In the GAI field, contextualization is absorbing and taking into account pertinent contextual data when producing out- puts. It entails comprehending the precise context, restrictions and needs related to the activity and using that information to deliver more precise, pertinent, and significant results. This includes user preferences, subject-matter expertise, task-specific requirements, input data, and activity-specific requirements. Considering these contextual elements, the model can give results that are more closely aligned with the specified criteria and appropriate for the specific application scenario.

Considering the issue’s wider context is another contextualization method. This may consider financial resources, time restraints, ethical and moral issues, and institutional rules. GAI models can produce accurate, useful, practical, and practicable results within the particular application setting by taking these contextual aspects into account. In health care, for instance, contextualization would entail adding pertinent research findings, medical advice, patient-specific data, and clinical protocols into the generative AI framework. By doing this, it would be feasible to ensure that the generated outputs, such as medical diagnoses, treatment recommendations, or patient records, are accurate, clinically relevant, and in line with best practices.

The results might not be coherent, relevant, or comply with particular constraints or rules without sufficient contextualization. GAI models are being advanced in terms of contextualization. Researchers are experimenting with methods that include utilizing pre-trained models in particular domains, adding external knowledge bases, focusing on task-specific data, and creating attention mechanisms that enable the model to concentrate on pertinent contextual information. These methods seek to improve the model’s capacity to produce more accurate, pertinent, and useful outputs across various applications.

3) DATA QUALITY AND BIAS

One of the significant limitations of GAI is the data quality and bias. The framework of GAI produces output based on the training data provided by health care records and medical writings; if the data supplied is biased or of poor quality, it will lead to inaccurate results. These data biases can creep into any development stage and come from several factors, including demographic disparities, variations in healthcare practices, and under-representation of specific populations. The GAI model can amplify these biases and perpetuate healthcare disparities and unequal treatment outcomes. Many generative AI applications in public deployment have already seen neglect in addressing bias. The data is unseeingly scraped from the internet without giving much attention to potential sources of misinformation or bias [82] or the training data is generated through unreliable sources [83].

Although responses from chatbots powered by LLM may seem creative, they simply reflect the model’s extensive analytical understanding of which words have been used before others in the text that it has already viewed. They cannot understand any language they use, including their responses and the prompts they are given. Models trained

TABLE 2. Types of content forms available that LLMs could analyze now and possible versions in the future.

Type of content	Potential applications	Availability
Image Analysis	Detecting and Analyzing images	Yes
Text / Conversations	Engaging into human-like conversations and giving reliable answers to question prompts	Yes
Sound	Sound based interactions and voice-to-text applications	No
Document/PDF Analysis	Summarising documents and analyzing research papers	No
Video	Text to video outputs based on prompts by user	Yes

on a large body of internet data with little filtering (such as ChatGPT or steady diffusion, for example) have absorbed facts and false information, biased and fair stuff, and hazardous and innocuous things. LLMs run the risk of duplicating, amplifying, and spreading bad content and false information without a way to evaluate any of these characteristics prior to responding to a prompt, as shown by many examples.

4) GENERALIZATION OF UNSEEN DATA

The generalization of unseen data is essential for GAI models to be reliable in real-world healthcare systems. However, this generalization can be affected due to various factors. If the generative AI models fail to update data over time or adapt to new medical trends, they will struggle to generalize to the current data distribution. Furthermore, the generative models are sensitive to variations and noise in the input data. This noise and variations can occur due to measurement errors or differences in imaging techniques. If the model cannot handle these issues, it will face performance issues when dealing with new data, which is different from training data. Furthermore, in healthcare, choosing the correct training data without infringement of copyrights or other ethical considerations while opting for optimum model performance is challenging.

5) PATIENT DATA PRIVACY

Patient data privacy is one of the major concerns in healthcare. In healthcare treatment, ambient sensors will collect patient data, including name, age, area of residence, medical history and other relevant information. The sensors may also capture information like the patient's voice, face, or heart rate, depending on the hardware. Information like this, if leaked, could lead to the exposure of patients' health status and their private information [84].

Furthermore, many patients receive in-house treatment or healthcare facilities considered free from sensors.For example, a patient might want to restrict monitoring a particular body part during a particular duration while using the bathroom. GAI models must adhere to this decisional privacy [85] and give the right to decide on their privacy and the amount of information they want to share.

The United States has data protection regulation- HIPAA to safeguard patient privacy. Generative AI models can be vulnerable to adversarial attacks. Malicious hackers can try to manipulate the models' outputs or get unauthorized access to sensitive information [86]. Countersecurity measures such as intrusion detection systems, encryption, and authentication must be implemented to avoid such attacks.

6) FALSE INFORMATION GENERATION

An LLM might occasionally reveal the truth or create infor- mation that is pertinent, acceptable, occasionally surprising, innovative, and appealing. Other times, it might generate or support the most flagrant and harmful falsehood. Second, the model cannot determine which one it is at any given moment, let alone alert the user. It is unsure whether the stuff it creates tells the truth or contains fabrications, misrepresentations, or objectionable material. Moreover, because LLMs are probabilistic algorithms, they may return different responses when given the same task or question more than once. These responses may be updated versions of previously incorrect or complicated answers, updated versions of incorrect answers that were previously correct, or combinations of these. This behaviour creates an issue with repeatability and reliability that necessitates ongoing human supervision of model operation.

7) INTEGRATION WITH CURRENT HEALTHCARE TECHNOLOGIES

Implementing generative AI models into the current health- care systems can be challenging. The generative models must be compatible with electronic health record (EHR) systems, clinical decision support tools, and other healthcare IT infrastructure. This integration can be complex and may require further study.To access real-time scenarios, generative AI models should be capable of processing data and generating outputs in real-time to ensure that healthcare professionals can make timely decisions. This real-time processing requires efficient computational infrastructure and optimized algorithms, which must be programmed appropriately before implementation.

8) COMPUTATIONAL COST

One significant factor to consider while integrating GAI into healthcare is cost. While implementing GAI is revolutionary, it may take a toll on the pocket. Training and building generative AI models require significant resources, expertise,

TABLE 3. Regulatory challenges in implementation of generative AI in healthcare.

Regulatory challenges	Description
Intellectual Property	Intellectual Property issues can be generated if GAI models create proprietary medical literature or research.
Medical Malpractice Liability	If recommendations given by GAI models bring harm to the patient when implemented, who should be held accountable? Healthcare professionals who used it, model engineers, or the institution that granted permission for usage.
Quality Control & Standardization	Consistency and reliability of recommendations made by GAI models need to be regulated as well as the data which is used to train the model.
Data Ownership	It is hard to justify who owns the data from which the LLMs learn. Concerns are raised when it comes to patients' data.
Continuous Monitoring & Validation	Ensuring continuous accuracy, performance and validity of GAI models over different categories at all times is a challenging task.
Informed Consent	It can be difficult for patients to understand the implications of GAI usage in their treatment; in every case, GAI is used, the patient must be informed of its pros and cons.
Interpretability & Transparency	Transparency must be maintained as to how and why a GAI model suggested a particular treatment. It can be difficult to explain every step taken by GAI model to patients.
Over-reliance on GAI Models	Over-reliance on GAI models can limit the need to consult professionals every now and then. It can lead to serious implications if the model malfunctions.

and computational infrastructure investment. It requires hiring AI technicians, investing in powerful hardware and software and acquiring large datasets for models to train on. While some resources require only a bigger initial payment, others supply recurring bills. These include upgrading the models, maintaining the hardware and addressing potential security vulnerabilities.

Furthermore, Healthcare professionals must be trained to integrate this technology into their daily dealings. Providing comprehensive training programs will incur costs associated with building a new curriculum, training sessions, and continuous learning initiatives.

9) LACK OF PROFESSIONAL EXPERTISE

It is important to note that generative AI models cannot replace professional human involvement. While the models can assist in decision-making, the responsibility of patient care must be taken by healthcare professionals, and recom- mendations by these models must be considered after proper validation by human clinicians. Guidelines and regulatory frameworks to address these ethical considerations must be established to govern the deployment and use of GAI models in healthcare.

10) ETHICS

Ethics plays a pivotal role in ensuring the responsibility and deployment of generative AI in healthcare, and the integration of AI into healthcare has introduced complex ethical considerations which must be taken into care to uphold patient privacy, fairness, accountability and overall well- being of the individual. Legal and ethical frameworks are mandatory to establish to prevent privacy concerns. Strict laws and governing bodies may protect a patient's overall treatment process. A recent high-profile lawsuit on Stable diffusion reveals the use of ''derivative works'' by OpenAI's models [87]. It suggests that LLM models use their work as a reference to generate images without the artist's consent, thus invoking copyright issues. These issues, if not dealt with, can affect patient treatment and harm the patient in the long run as these practices will not be limited to copyrights but may also extend to the patient's consent. One major factor in ethical considerations is transparency. In the current scenario, a user cannot tell if the output provided by GAI models on user prompts is true without any external assistance. It has been noted that some GAI models, such as Galactica AI, displayed made-up citations and papers [88]. If such models are used without proper checking, it will lead to misdiagnosis and fatal treatment. In addition to these, Table 3 [18] lists various regulatory challenges that must be considered when implementing generative AI in healthcare [82].

Apart from the above challenges, there is also a chance that excessive dependence on LLMs will result in the undervaluation of clinical judgment and human competence. While LLMs can support decision-making, they should not replace a healthcare professional's knowledge, experience, or capacity for critical thought. It is crucial to balance the capabilities of LLMs and the engagement of human professionals to maintain patient safety and the best possible healthcare outcomes. GAI researchers, medical experts, ethicists, and regulatory agencies must continue to work together on research, development, and collaborative projects to address these limitations. To maximize the advantages of LLMs while minimizing their drawbacks and potential

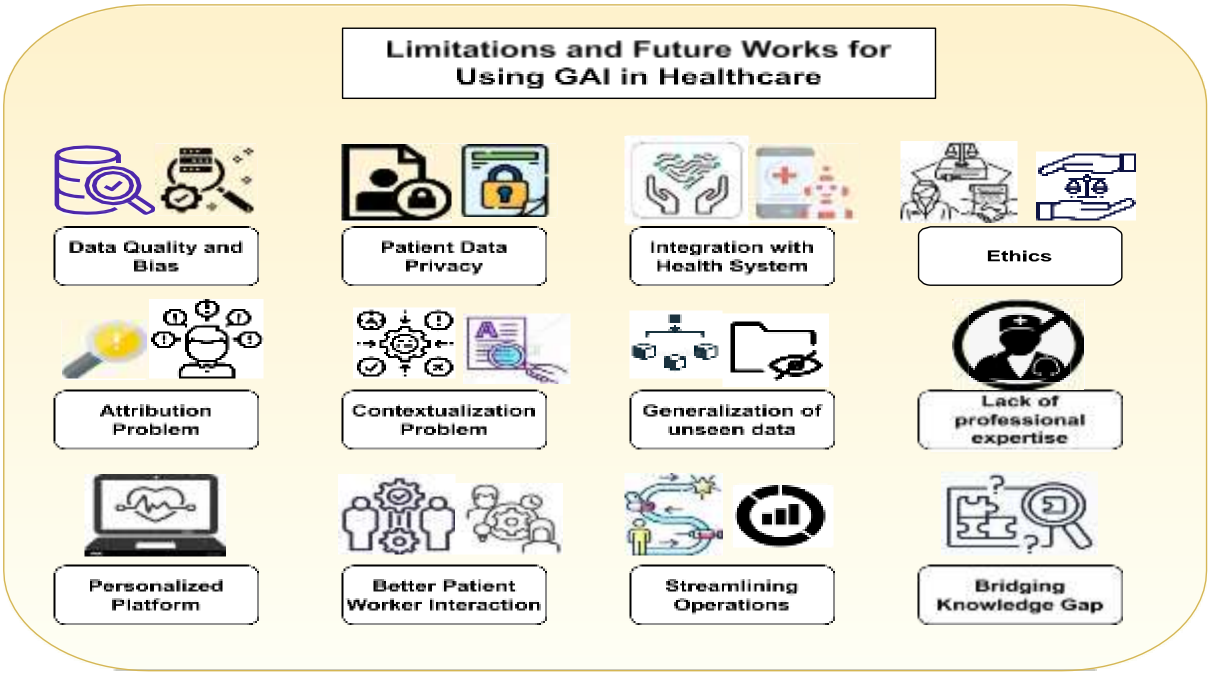

FIGURE 8. Limitations and future work.

risks in future healthcare applications, transparent standards, strong validation processes, and strict ethical frameworks are essential. These should be seen as inadequate machines that have the potential to greatly increase process efficiency but necessitate tight human oversight and intervention at all operational interfaces, including input and output.

VIII. FUTURE RESEARCH DIRECTIONS

GAI applications that create new content in response to textual instructions, including text, images, audio, code, and videos, heavily rely on large language models. These GAI applications can become techniques with significant potential for spreading false information or damaging and erroneous content at an unprecedented scale without human oversight, guidance, and responsible design and operation. They could, however, develop into extremely effective, reliable aids for information management provided they are positioned and developed responsibly as companions in offering support to people, enhancing but not replacing their role in decision- making, knowledge retrieval, and other cognitive processes. Enhancing these models' clinical decision-support skills is becoming increasingly a priority. In this section, we present future directions for research in GAI for healthcare.

A. CUSTOMIZED/PERSONALIZED SUGGESTIONS AND A PLATFORM FOR INFORMATION EXCHANGE

LLMs can be progressively improved to provide more precise and individualized suggestions for diagnosis, therapy planning, and patient outcome monitoring. These models can deliver timely and context-aware insights to health- care practitioners, improving clinical decision-making. They incorporate real-time patient data, such as electronic health records and information from wearable devices. LLMs may also help professionals in the healthcare industry collaborate across disciplines and share knowledge. These models can work as a shared platform for information exchange, enabling practitioners from different disciplines to interact and gain from each other's experience. They are accessible to many practitioners, including doctors, nurses, and allied healthcare professionals. This partnership may result in more thorough and all-encompassing patient care and a culture of ongoing learning and development among healthcare professionals.

B. ENHANCED PATIENT AND WORKER INTERACTIONS

Enhancing LLMs' natural language comprehension abilities to understand better medical jargon, contextual nuances, and patient-specific information is another topic of future efforts. This would allow patients and virtual assistants powered by these models to interact more successfully. Patients could provide precise information about their med- ical conditions, receive explanations and recommendations specific to their needs, and even have dialogues that resemble human interactions. This could enhance patient education, involvement, and informational access to healthcare. LLMs could also help with cross-language communication and multilingual healthcare encounters. These models' ability to translate between languages can assist healthcare workers and patients who speak different languages to commu- nicate more effectively. Ensuring accurate and effective communication between patients and healthcare practitioners might considerably increase access to healthcare services, especially in multicultural and diverse areas.

C. STREAMLINING ADMINISTRATIVE OPERATIONS

LLMs can also help the healthcare sector's administrative operations run more smoothly. They can streamline and automate tasks like invoicing, coding, and medical documentation, giving healthcare workers more time to provide direct patient care. These models can help create precise and uniform clinical notes, summarise patient encounters, and extract pertinent data from medical records, improving efficiency and easing administrative stress.LLMs may one day be essential to advancing medical science. They can help with information synthesis, literature reviews, and finding patterns or relationships in the massive body of biological literature. These models could help with drug discovery and repurposing initiatives, advancing personalized medical techniques, and accelerating scientific advancements.

D. ENHANCING DECISION MAKING AND BRIDGING THE KNOWLEDGE GAP

LLMs can also close the time gap between the limited time available to healthcare professionals and the continually developing body of medical knowledge. Keeping up with the most recent research can be difficult for busy practitioners due to the constant influx of new research papers, clinical trials, and treatment guidelines. On the other hand, LLMs may continuously study and analyze the most recent data, guaranteeing that healthcare professionals have access to the most up-to-date and pertinent insights. This modern information integration raises the standard of care by enabling practitioners to make educated judgments based on the most recent data.

IX. CONCLUSION

GAI models, recently catching attention, have promising potential in healthcare. This paper has discussed various applications in which different GAI models enhanced health- care operations. The diverse applications, including medical imaging, drug discovery, personalized patient treatment, medical simulation and training, clinical trial optimization, mental health support, healthcare operations and resource management, chatbots, human movement simulation and analysis and text generation and summarization indicate how flexible and reliable this technology is and how it can be implemented in healthcare. The different use cases discussed show how GAI has been used to aid patients suffering from visual snow syndrome and enhance the molecular optimisation process. Further, how GAI is used in Medical Education and Dentistry has also been showcased. However, despite the gains, there continue to be challenges associated with applying GAI in healthcare. Ethics, including patient privacy and data security, must be prioritized. Stringent laws and safety measures must be in place to ensure the appropriate and secure use of patient information. More study and analysis are required to utilise GAI's power in regular healthcare practices properly. Collaboration between AI scientists, healthcare practitioners, and legislators is essential to solve technological constraints, validate models and smoothly integrate GAI into current healthcare systems.

REFERENCES

[1] L. Floridi and M. Chiriatti, ''GPT-3: Its nature, scope, limits, and consequences,'' *Minds Mach.*, vol. 30, no. 4, pp. 681–694, Dec. 2020.

[2] G. Marcus, E. Davis, and S. Aaronson, ''A very preliminary analysis of DALL-E 2,'' 2022, *arXiv:2204.13807*.

[3] *Midjourney*. Accessed: Jan. 23, 2024. [Online]. Available: https://www. midjourney.com/home/?callbackUrl=%2Fapp%2F

[4] *Stable Diffusion*. Accessed: Jan. 23, 2024. [Online]. Available: https:// stablediffusionweb.com/

[5] J. Zhang, Y. Peng, and M. Yuan, ''Unsupervised generative adversarial cross-modal hashing,'' in *Proc. AAAI Conf. Artif. Intell.*, Apr. 2018, vol. 32, no. 1, pp. 1–8.

[6] D. Baidoo-Anu and L. O. Ansah, ''Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning,'' *J. AI*, vol. 7, no. 1, pp. 52–62, Dec. 2023.

[7] O. Temsah, S. A. Khan, Y. Chaiah, A. Senjab, K. Alhasan, A. Jamal, F. Aljamaan, K. H. Malki, R. Halwani, J. A. Al-Tawfiq, M.-H. Temsah, and A. Al-Eyadhy, ''Overview of early ChatGPT's presence in medical literature: Insights from a hybrid literature review by ChatGPT and human experts,'' *Cureus*, vol. 15, no. 4, Apr. 2023.

[8] *Diagnamed Launches a Generative Artificial Intelligence Medical Chatbot, Dr. GenAI*. Accessed: Jun. 19, 2023. [Online]. Available: https://aithority.com/machine-learning/diagnamed-launches-a-generative- artificial-intelligence-medical-chatbot-dr-genai/

[9] M. S. Abdel-Messih and M. N. K. Boulos, ''ChatGPT in clinical toxicology,'' *JMIR Med. Educ.*, vol. 9, Mar. 2023, Art. no. e46876.

[10] M. Sallam, ''ChatGPT utility in healthcare education, research, and practice: Systematic review on the promising perspectives and valid concerns,'' *Healthcare*, vol. 11, no. 6, p. 887, Mar. 2023.

[11] T. N. Y. Times. (2023). *Generative AI Start-up Cohere Valued at About $2 Billion in Funding Round*. [Online]. Available: https://www. nytimes.com/2023/05/02/technology/generative-ai-start-up-coherefunding.html

[12] R. Mao, G. Chen, X. Zhang, F. Guerin, and E. Cambria, ''GPTEval: A sur- vey on assessments of ChatGPT and GPT-4,'' 2023, *arXiv:2308.12488*.

[13] T. H. Kung, M. Cheatham, A. Medenilla, C. Sillos, L. De Leon, C. Elepaño, M. Madriaga, R. Aggabao, G. Diaz-Candido, J. Maningo, and V. Tseng, ''Performance of ChatGPT on USMLE: Potential for AI-assisted medical education using large language models,'' *PLOS Digit. Health*, vol. 2, no. 2, Feb. 2023, Art. no. e0000198.

[14] O. AI. (2023). *Gpt-4 is Openai's Most Advanced System, Producing Safer and More Useful Responses*. [Online]. Available: https://openai.com/gpt-4

[15] S. Teebagy, L. Colwell, E. Wood, A. Yaghy, and M. Faustina, ''Improved performance of ChatGPT-4 on the OKAP exam: A comparative study with ChatGPT-3.5,'' *medRxiv*, Apr. 2023.

[16] G. A. Johnson, J. N. Bloom, L. Szczotka-Flynn, D. Zauner, and R. L. Tomsak, ''A comparative study of resident performance on stan- dardized training examinations and the American board of ophthalmology written examination,'' *Ophthalmology*, vol. 117, no. 12, pp. 2435–2439, Dec. 2010.

[17] R. Bhayana, S. Krishna, and R. R. Bleakney, ''Performance of ChatGPT on a radiology board-style examination: Insights into current strengths and limitations,'' *Radiology*, vol. 307, no. 5, Jun. 2023, Art. no. 230582.

[18] B. Meskó and E. J. Topol, ''The imperative for regulatory oversight of large language models (or generative AI) in healthcare,'' *npj Digit. Med.*, vol. 6, no. 1, p. 120, Jul. 2023.

[19] R. Rothbaum and J. McGee, ''Aquagenic urticaria: Diagnostic and man- agement challenges,'' *J. Asthma Allergy*, vol. 9, pp. 209–213, Nov. 2016.

[20] J. T. Ludlow, R. G. Wilkerson, and T. M. Nappe, ''Methemoglobinemia,'' Tech. Rep., 2019.

[21] Y. Yang, H. Fu, A. I. Aviles-Rivero, C.-B. Schönlieb, and L. Zhu, ''DiffMIC: Dual-guidance diffusion network for medical image classifica- tion,'' in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent.* Springer, 2023, pp. 95–105.

[22] X. Bing, W. Zhang, L. Zheng, and Y. Zhang, ''Medical image super resolution using improved generative adversarial networks,'' *IEEE Access*, vol. 7, pp. 145030–145038, 2019.

[23] J. S. Yoon, C. Zhang, H.-I. Suk, J. Guo, and X. Li, ''SADM: Sequence-aware diffusion model for longitudinal medical image gen- eration,'' in *Proc. Int. Conf. Inf. Process. Med. Imag.* Springer, 2023, pp. 388–400.

[24] T. Susnjak, ''Beyond predictive learning analytics modelling and onto explainable artificial intelligence with prescriptive analytics and Chat- GPT,'' *Int. J. Artif. Intell. Educ.*, pp. 1–31, Jun. 2023.

[25] C. Molnar, G. Casalicchio, and B. Bischl, ''Interpretable machine learning—A brief history, state-of-the-art and challenges,'' in *Proc. Joint Eur. Conf. Mach. Learn. Knowl. Discovery Databases*. Springer, 2020, pp. 417–431.

[26] M. T. Ribeiro, S. Singh, and C. Guestrin, ''Anchors: High-precision model- agnostic explanations,'' in *Proc. AAAI Conf. Artif. Intell.*, 2018, vol. 32, no. 1, pp. 1–9.

[27] Y. Li, J. Pei, and L. Lai, ''Structure-based de novo drug design using 3D deep generative models,'' *Chem. Sci.*, vol. 12, no. 41, pp. 13664–13675, 2021.

[28] T. Salimans, I. Goodfellow, W. Zaremba, V. Cheung, A. Radford, and X. Chen, ''Improved techniques for training GANs,'' in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 29, 2016, pp. 1–9.

[29] H. Abdine, M. Chatzianastasis, C. Bouyioukos, and M. Vazirgiannis, ''Prot2Text: Multimodal protein's function generation with GNNs and transformers,'' 2023, *arXiv:2307.14367*.

[30] C. Buche, F. Lasson, and S. Kerdelo, ''Conditional autoencoder pre-training and optimization algorithms for personalized care of hemophiliac patients,'' *Frontiers Artif. Intell.*, vol. 6, Jan. 2023, Art. no. 1048010.

[31] H. Luo, K. Nagano, H.-W. Kung, Q. Xu, Z. Wang, L. Wei, L. Hu, and H. Li, ''Normalized avatar synthesis using StyleGAN and perceptual refinement,'' in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2021, pp. 11657–11667.

[32] J. Mueller, R. B. Parikh, and A. Noble, ''Evaluating clinical trial inclu- sion/exclusion criteria from claims using generative artificial intelligence,'' Tech. Rep., 2023.

[33] L. Gootjes-Dreesbach, M. Sood, A. Sahay, M. Hofmann-Apitius, and H. Fröhlich, ''Variational autoencoder modular Bayesian networks for simulation of heterogeneous clinical study data,'' *Frontiers Big Data*, vol. 3, p. 16, May 2020.

[34] L. Yang, ''Multi-modal depression detection and estimation,'' in *Proc. 8th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW)*, Sep. 2019, pp. 26–30.

[35] *Revolutionizing Mental Health: Generative AI in Therapy*. Accessed: Dec. 11, 2023. [Online]. Available: https://www.productiveedge.com/blog/revolutionizing-mental-health-generative-ai-and-therapy

[36] *Generative ai for Mental Health is Upping the Ante by Going Multi-Modal, Embracing E-Wearables, and a Whole Lot More*. Accessed: Dec. 11, 2023. [Online]. Available: https://www.forbes.com/sites/lanceeliot/ 2023/11/02/generative-ai-for-mental-health-is-upping-the-ante-by-going- multi-modal-embracing-e-wearables-and-a-whole-lot-more/

[37] M. Barat, P. Soyer, and A. Dohan, ''Appropriateness of recommendations provided by ChatGPT to interventional radiologists,'' *Can. Assoc. Radiologists J.*, vol. 74, no. 4, pp. 758–763, Nov. 2023.

[38] T. Dave, S. A. Athaluri, and S. Singh, ''ChatGPT in medicine: An overview of its applications, advantages, limitations, future prospects, and ethical considerations,'' *Frontiers Artif. Intell.*, vol. 6, May 2023, Art. no. 1169595.

[39] H. Lee, ''The rise of ChatGPT: Exploring its potential in medical education,'' *Anatomical Sci. Educ.*, Mar. 2023.

[40] *What is Instructgpt and How to Access Instruct Gpt?* Accessed: Jun. 29, 2023. [Online]. Available: https://www.theinsaneapp.com/2023/05/ everything-about-instructgpt.html

[41] *AI Ushers in Next-gen Prior Authorization in Healthcare | Mckinsey | Mckinsey*. Accessed: Jul. 17, 2023. [Online]. Available: https://www.mckinsey.com/industries/healthcare/our-insights/ai-ushers- in-next-gen-prior-authorization-in-healthcare

[42] *Triage—An Overview | Sciencedirect Topics*. Accessed: Jul. 17, 2023. [Online]. Available: https://www.sciencedirect.com/topics/medicine-and-dentistry/triage

[43] J. Huang, L. Neill, M. Wittbrodt, D. Melnick, M. Klug, M. Thompson, J. Bailitz, T. Loftus, S. Malik, A. Phull, V. Weston, J. A. Heller, and M. Etemadi, ''Generative artificial intelligence for chest radiograph interpretation in the emergency department,'' *JAMA Netw. Open*, vol. 6, no. 10, Oct. 2023, Art. no. e2336100.

[44] *Safely Harness the Power of Generative ai in Healthcare With Clinically Validated Virtual Triage*. Accessed: Jul. 17, 2023. [Online]. Available: https://www.prnewswire.com/news-releases/safely-harness-the-power-of-generative-ai-in-healthcare-with-clinically-validated-virtual-triage-301811636.html

[45] D. M. Levine, R. Tuwani, B. Kompa, A. Varma, S. G. Finlayson, A. Mehrotra, and A. Beam, ''The diagnostic and triage accuracy of the GPT-3 artificial intelligence model,'' *medRxiv*, Jan. 2023.

[46] A. Jadon and S. Kumar, ''Leveraging generative AI models for synthetic data generation in healthcare: Balancing research and privacy,'' 2023, *arXiv:2305.05247*.

[47] H. Mischak, G. Allmaier, R. Apweiler, T. Attwood, M. Baumann, A. Benigni, S. E. Bennett, R. Bischoff, E. Bongcam-Rudloff, and G. Capasso, ''Recommendations for biomarker identification and quali- fication in clinical proteomics,'' *Sci. Transl. Med.*, vol. 2, no. 46, 2010, Art. no. 46ps42.

[48] R. Nair, D. D. Mohan, S. Frank, S. Setlur, V. Govindaraju, and M. Ramanathan, ''Generative adversarial networks for modelling clinical biomarker profiles with race/ethnicity,'' *Brit. J. Clin. Pharmacol.*, vol. 89, no. 5, pp. 1588–1600, May 2023.

[49] O. Zaballa, A. Pérez, E. G. Inhiesto, T. A. Ayesta, and J. A. Lozano, ''Learning the progression patterns of treatments using a probabilistic gen- erative model,'' *J. Biomed. Informat.*, vol. 137, Jan. 2023, Art. no. 104271.

[50] Q. Liu, E. Fuster-Garcia, I. T. Hovden, D. Sederevicius, K. Skogen, B. J MacIntosh, E. Grødem, T. Schellhorn, P. Brandal, A. Bjørnerud, and K. E. Emblem, ''Treatment-aware diffusion probabilistic model for longitudinal MRI generation and diffuse glioma growth prediction,'' 2023, *arXiv:2309.05406*.

[51] K. Singhal, S. Azizi, T. Tu, S. S. Mahdavi, J. Wei, H. W. Chung, N. Scales, A. Tanwani, H. Cole-Lewis, S. Pfohl, and P. Payne, ''Large language models encode clinical knowledge,'' 2022, *arXiv:2212.13138*.

[52] K. Singhal, T. Tu, J. Gottweis, R. Sayres, E. Wulczyn, L. Hou, K. Clark, S. Pfohl, H. Cole-Lewis, and D. Neal, ''Towards expert- level medical question answering with large language models,'' 2023, *arXiv:2305.09617*.

[53] H. Bair and J. Norden, ''Large language models and their implications on medical education,'' *Academic Med.*, May 2023.

[54] *Health AI Research LLM Updates*. Accessed: Jun. 28, 2023. [Online]. Available: https://blog.google/technology/health/ai-llm-medpalm- research-thecheckup/

[55] *Med-Palm*. Accessed: Jul. 14, 2023. [Online]. Available: https://sites. research.google/med-palm/

[56] R. Luo, L. Sun, Y. Xia, T. Qin, S. Zhang, H. Poon, and T.-Y. Liu, ''BioGPT: Generative pre-trained transformer for biomedical text generation and mining,'' *Briefings Bioinf.*, vol. 23, no. 6, Nov. 2022.

[57] Z. Jie, Z. Zhiying, and L. Li, ''A meta-analysis of Watson for oncology in clinical application,'' *Sci. Rep.*, vol. 11, no. 1, p. 5792, Mar. 2021.

[58] Z. Dlamini, F. Z. Francies, R. Hull, and R. Marima, ''Artificial intelligence (AI) and big data in cancer and precision oncology,'' *Comput. Struct. Biotechnol. J.*, vol. 18, pp. 2300–2311, 2020.

[59] *Intelligent Computing for Healthcare | Nvidia Clara*. Accessed: Jul. 17, 2023. [Online]. Available: https://www.nvidia.com/en-in/clara/

[60] *Healthcare Developer Resources | Nvidia Developer*. Accessed: Jul. 17, 2023. [Online]. Available: https://developer.nvidia.com/ industries/healthcare

[61] *Deep Health | Radiology AI Machine Learning Solutions*. Accessed: Jul. 17, 2023. [Online]. Available: https://deephealth.com/

[62] *Deephealth: A Deep Learning Solution for the COVID-19 Crisis | By Pablo Castañeda | Saturdays.ai | Medium*. Accessed: Jul. 17, 2023. [Online]. Available: https://medium.com/saturdays-ai/deephealth-a-deep-learning-solution-for-the-covid-19-crisis-785238119c1a

[63] A. S. Panayides, A. Amini, N. D. Filipovic, A. Sharma, S. A. Tsaftaris, A. Young, D. Foran, N. Do, S. Golemati, T. Kurc, K. Huang, K. S. Nikita, B. P. Veasey, M. Zervakis, J. H. Saltz, and C. S. Pattichis, ''AI in medical imaging informatics: Current challenges and future directions,'' *IEEE J. Biomed. Health Informat.*, vol. 24, no. 7, pp. 1837–1857, Jul. 2020.

[64] J. Lee, W. Yoon, S. Kim, D. Kim, S. Kim, C. H. So, and J. Kang, ''BioBERT: A pre-trained biomedical language representation model for biomedical text mining,'' *Bioinformatics*, vol. 36, no. 4, pp. 1234–1240, Feb. 2020.

[65] A. Kormilitzin, N. Vaci, Q. Liu, and A. Nevado-Holgado, ''MED7: A transferable clinical natural language processing model for electronic health records,'' *Artif. Intell. Med.*, vol. 118, Aug. 2021, Art. no. 102086.

[66] F. Puledda, C. Schankin, K. Digre, and P. J. Goadsby, ''Visual snow syndrome: What we know so far,'' *Current Opinion Neurol.*, vol. 31, no. 1, pp. 52–58, 2018.
[67] M. Balas and J. A. Micieli, ''Visual snow syndrome: Use of text-to-image artificial intelligence models to improve the patient perspective,'' *Can. J. Neurological Sci./J. Canadien des Sci. Neurologiques*, vol. 50, no. 6, pp. 946–947, Nov. 2023.
[68] J. Avorn, ''The $2.6 billion pill—Methodologic and policy consid- erations,'' *New England J. Med.*, vol. 372, no. 20, pp. 1877–1879, 2015.
[69] L. Maziarka, A. Pocha, J. Kaczmarczyk, K. Rataj, T. Danel, and M. Warchol, ''Mol-CycleGAN: A generative model for molecular optimization,'' *J. Cheminformatics*, vol. 12, no. 1, pp. 1–18, Dec. 2020.
[70] M. H. S. Segler, T. Kogej, C. Tyrchan, and M. P. Waller, ''Generating focused molecule libraries for drug discovery with recurrent neural networks,'' *ACS Central Sci.*, vol. 4, no. 1, pp. 120–131, Jan. 2018.
[71] F. Grisoni, B. J. H. Huisman, A. L. Button, M. Moret, K. Atz, D. Merk, and G. Schneider, ''Combining generative artificial intelligence and on- chip synthesis for de novo drug design,'' *Sci. Adv.*, vol. 7, no. 24, Jun. 2021, Art. no. eabg3338.
[72] V. Bagal, R. Aggarwal, P. K. Vinod, and U. D. Priyakumar, ''MolGPT: Molecular generation using a transformer-decoder model,'' *J. Chem. Inf. Model.*, vol. 62, no. 9, pp. 2064–2076, May 2022.
[73] J. G. Ruiz, M. J. Mintzer, and R. M. Leipzig, ''The impact of e-learning in medical education,'' *Academic Med.*, vol. 81, no. 3, pp. 207–212, 2006.
[74] M. Karabacak, B. B. Ozkara, K. Margetis, M. Wintermark, and S. Bisdas, ''The advent of generative language models in medical education,'' *JMIR Med. Educ.*, vol. 9, Jun. 2023, Art. no. e48163.
[75] Y. Okuda, E. O. Bryson, S. DeMaria, L. Jacobson, J. Quinones, B. Shen, and A. I. Levine, ''The utility of simulation in medical education: What is the evidence?'' *Mount Sinai J. Medicine: A J. Translational Personalized Med.*, vol. 76, no. 4, pp. 330–343, Aug. 2009.
[76] *What is Persim—Medcognition*. Accessed: Jun. 29, 2023. [Online]. Available: https://medcognition.com/what-is-persim/
[77] *20230624-22994-cporbe.pdf*. Accessed: Jul. 14, 2023. [Online]. Available: https://assets.cureus.com/uploads/review_article/pdf/158756/20230624- 22994-cporbe.pdf
[78] (2016). *In 2016, Microsoft's Racist Chatbot Revealed the Dangers of Online Conversation—IEEE Spectrum*. Accessed: Jun. 29, 2023. [Online]. Available: https://spectrum.ieee.org/in-2016-microsofts-racist-chatbot-revealed-the-dangers-of-online-conversation
[79] H. M. Alhaidry, B. Fatani, J. O. Alrayes, A. M. Almana, N. K. Alfhaed, H. Alhaidry, J. Alrayes, A. Almana, and N. K. A. Sr, ''ChatGPT in dentistry: A comprehensive review,'' *Cureus*, vol. 15, no. 4, 2023.
[80] T. T. Nguyen, N. Larrivée, A. Lee, O. Bilaniuk, and R. Durand, ''Use of artificial intelligence in dentistry: Current clinical trends and research advances,'' *J. Can Dent. Assoc.*, vol. 87, no. l7, pp. 1488–2159, 2021.
[81] *The Attribution Problem With Generative AI—Hacking Semantics*. Accessed: Jul. 17, 2023. [Online]. Available: https://hackingsemantics. xyz/2022/attribution/
[82] S. Harrer, ''Attention is not all you need: The complicated case of ethically using large language models in healthcare and medicine,'' *eBioMedicine*, vol. 90, Apr. 2023, Art. no. 104512.
[83] B. Perrigo, ''OpenAI used Kenyan workers on less than 2 dollars per hour to make CHATGPT less toxic time,'' Tech. Rep., 2023.
[84] N. Martinez-Martin, Z. Luo, A. Kaushal, E. Adeli, A. Haque, S. S. Kelly, S. Wieten, M. K. Cho, D. Magnus, L. Fei-Fei, K. Schulman, and A. Milstein, ''Ethical issues in using ambient intelligence in health-care settings,'' *Lancet Digit. Health*, vol. 3, no. 2, pp. 115–123, Feb. 2021.
[85] A. L. Allen, ''Coercing privacy,'' *Wm. Mary L, Rev.*, vol. 40, p. 723, Jan. 1998.
[86] J. Deng and Y. Lin, ''The benefits and challenges of ChatGPT: An overview,'' *Frontiers Comput. Intell. Syst.*, vol. 2, no. 2, pp. 81–83, Jan. 2023.
[87] S. Goldman. (2023). *Stable Diffusion AI Art Lawsuit, Plus Caution From Openai, Deepmind | the AI Beat*. [Online]. Available: https://venturebeat. com/ai/stable-diffusion-lawsuit-plus-words-of-caution-from-openai- deepmind-the-ai-beat/
[88] P. J. B. Aaron and J. Snoswell. (2022). *A Galaxy of Deep Science Fakes: The Problems With Galactica AI*. [Online]. Available: https://www. siliconrepublic.com/machines/galactica-ai-meta-fake-science-misinformation

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