Global Journal of Modeling and Intelligent Computing
(GJMIC)

Vol. 3, No. 2, July, 2023 ISSN: 2767-1917

GENERATIVE AI INNOVATIONS IN HEALTHCARE SYSTEM AND ITS USES

Anjli Barman, Atal Bihari Vajpayee University Bilaspur, Chhattisgarh, India (anjlibarman5@gmail.com)

ABSTRACT

Generative AI is significantly altering patient care and research, and it is redefining the field of healthcare. Generative AI's advanced abilities are improving medication research, treatment strategies, and diagnostics. Artificial intelligence integration is improving patient outcomes, allocating resources optimally, and creating more personalized and effective healthcare solutions. Researchers and healthcare professionals are using Generative AI to extract fresh insights from large datasets, accelerating advancements in medicine. Examine how Generative AI is revolutionizing healthcare to improve research and provide personalized patient care. The promise of Generative AI to revolutionize health is only getting started. Learn how this strong technology may help the healthcare revolution industry achieve previously unobtainable levels of efficiency, effectiveness, and creativity. You can also investigate a framework to assist your organization in reaching its full potential. While machine learning and natural language processing have been used in a variety of healthcare use cases in recent years, new generative AI models are pushing the boundaries of healthcare technology. In terms of natural language development, summarization, translation, reasoning, insight retrieval, and handling unstructured, unlabelled information, these models exhibit previously unheard-of capabilities. Personalization in healthcare could be made possible by generative AI technology, which can democratize knowledge, improve interoperability, and speed up discovery.

Keywords: Artificial Intelligence, Generative AI, Healthcare, Machine Learning, Natural Language Processing, Patient Care.

1. INTRODUCTION

The healthcare areas faces many challenges, including the increasing demand for personalized medicine [1], the need to protect patient privacy when using their data for research [2], increasing healthcare costs [3], the commitment to providing high-quality patient care [4], the shortage of healthcare professionals [5], the management of chronic diseases [6], and the overall goal of improving diagnostic accuracy and treatment outcomes [7]. Additionally, medical failures represent a major public health concern and are one of the leading causes of death. These avoidable adverse events can occur during health care and include issues such as erroneous blood transfusions, misdiagnoses, instances of undertreatment or overtreatment, surgical errors, self-harm, and even death. Moreover, the healthcare industry is undergoing growing technological advancements and the creation of large datasets across various healthcare databases. Despite this wealth of data, there has been minimal effort to leverage it for disease prevention [8]. Implementing health technologies could help address these challenges. Artificial intelligence (AI) and medicine have integrated to develop innovative solutions for clinical settings in our rapidly evolving digital landscape. Over the past decade, there has been a significant increase in the use of AI in healthcare.

The introduction of AI holds tremendous potential to enhance healthcare outcomes, improve access, and reduce costs. AI is a cutting-edge technology that can elevate clinical diagnosis, medical decision-making, and treatment. The wide-ranging applications of AI in healthcare highlight its versatility, including image-based diagnosis in fields such as radiology, ophthalmology, pathology, and dermatology; genomic data interpretation; clinical forecasting; biomarker identification; and robotic surgery. For example, AI is currently used to predict patient mortality rates, enhance robotic surgeries, decrease false-positive results in breast cancer screenings, and streamline physicians' operational procedures. Furthermore, applications in healthcare AI can be expanded through generative artificial intelligence (GAI). GAI is a powerful approach that produces new content across various formats, such as text, images, audio, code, and video. Its versatility has made it popular in numerous fields, and recently, it has gained significant attention in healthcare, emerging as a thriving area of research. Numerous studies have demonstrated that generative AI can be applied in various disciplines, including medical diagnosis, treatment, prognosis, clinical documentation, medical education, and the summarization of evidence-based medicine.

The full range of generative AI applications remains largely unknown, though it has garnered significant attention in healthcare research. Despite their potential benefits for the healthcare industry, generative models present several challenges and ethical concerns. It is essential to ensure the accuracy of AI-generated decisions, especially in critical medical situations. There is a need for improved transparency and explainability, as the complexity and opacity of many AI models, particularly generative ones, can complicate their interpretations. Ethical considerations, such as patient confidentiality, data privacy, and bias reduction in AI models, must be given careful attention. To maintain public trust in AI-driven healthcare innovations, it is vital to safeguard the confidentiality and integrity of medical data.

To our knowledge, there has been limited research exploring the advantages, challenges, and applications of generative AI in the healthcare sector. However, our work presents a unique contribution by specifically focusing on these aspects within the broader health landscape. While some publications provide valuable insights into the use of generative AI in healthcare, our analysis delves deeper into the complex issues faced by the health sector. Unlike previous studies that mostly concentrate on the application of generative AI in clinical decision support and summarize ongoing business and research initiatives, our goal is to provide a comprehensive examination of how generative AI technologies are applied across various healthcare domains. We aim to address challenges ranging from personalized treatment recommendations to diagnostic support. By evaluating the current state of research, implementations, and outcomes, our work seeks to enhance understanding of the transformative impact of generative AI in healthcare and to establish a foundation for future studies into its potential and applications.

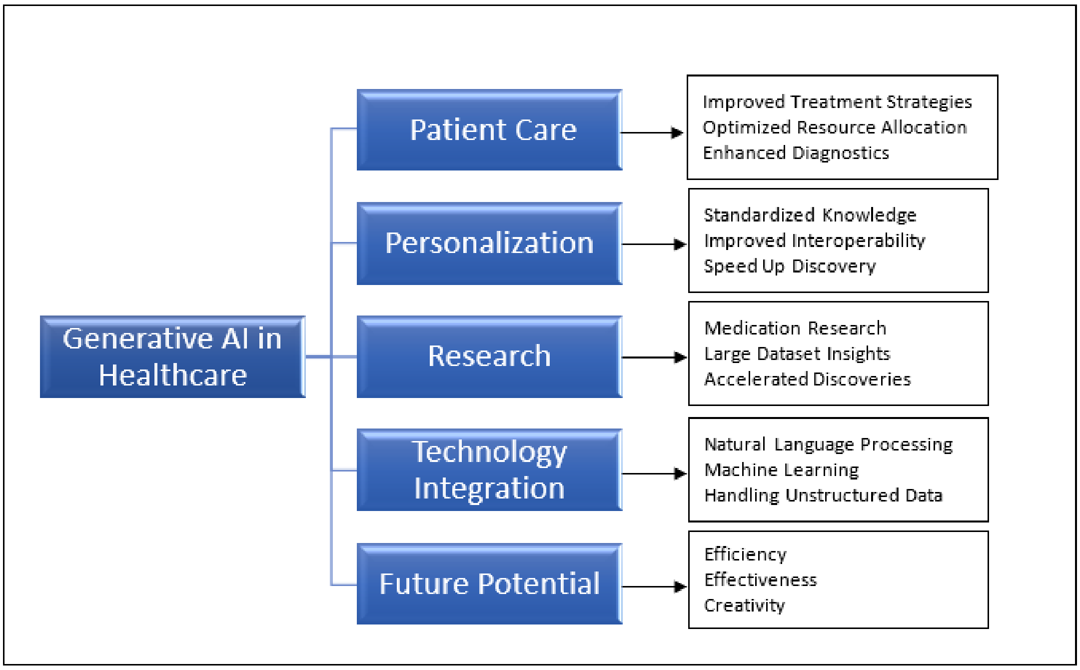

Figure 1: Generative AI in Healthcare

1.1 GENERATIVE AI MODELS

The most popular generative models and their use cases. We will also look into how they conduct AI research and train to produce better results.

Generative Adversarial Network (GAN)

Generative adversarial networks (GANs) consist of two neural networks: a generator that creates synthetic data and a discriminator that attempts to distinguish between real and fake data. In simple terms, a creator competes with a critic to produce more realistic and creative outputs. This competition resembles a training process, where the generator improves continuously based on the feedback from the discriminator. GANs are particularly effective at creating images. In addition to generating content, they can also be used to design new characters or create photorealistic portraits.

Variational Autoencoder (VAE)

The variational autoencoder model consists of two main components. The first component is the encoder, which breaks down input data into very small parts. This analysis enables the decoder to synthesize new content from those tiny fragments. The second component, the decoder, functions like a creative writer. It takes the key points identified by the encoder and uses them to generate new content, similar to crafting an entirely new story based on a book summary. VAEs are particularly useful for tasks such as data analysis, compression, and rapid content creation. However, the quality of the outputs generated by this model heavily depends on the complexity of the input data.

Transformer-Based Models
This AI technology is built on large language models that allow it to understand and interpret human language. Utilizing transformer architecture and a self-attention mechanism, these generative models can focus on all words at once, regardless of their position in the text or the length of the text itself. As a result, it can assist you with various writing-related tasks, including translating, answering questions, and conducting research by analysing vast amounts of raw data. Additionally, generative AI can create different types of text from scratch, such as research papers, movie scripts, or even humorous social media posts. A well-known example of such a tool is Chat GPT, which generates responses based on the input text.

Autoregressive Models
Unlike transformer-based approaches, autoregressive models analyze text one sequence at a time rather than focusing on all the words simultaneously. As a result, these models may perform better with shorter text forms. Because they rely solely on the preceding phrases, they might struggle to understand the entire text at once. In contrast, transformer-based models may overlook certain relationships between sequential phrases. In simple terms, autoregressive models function like careful storytellers who construct narratives piece by piece based on the training data they have.

Diffusion Models
Diffusion models differ from transformer-based or autoregressive AI systems in that they do not predict the next token based on previous information. Instead, generative AI in diffusion models focuses on how information gradually spreads through a sequence of data. These models typically employ denoising score-matching techniques to comprehend the entire process step-by-step. As a result, diffusion technology excels at producing high-quality content, particularly images and videos. However, training diffusion models requires substantial computational resources due to the complexity of the model architecture.

1.2 APPLICATIONS OF GENERATIVE AI IN HEALTHCARE

Medical Imaging: Generative AI has proven highly effective in improving medical imaging processes. It can reconstruct high-resolution images from low-resolution scans and generate synthetic medical images for training purposes. Generative Adversarial Networks (GANs), in particular, have been utilized to create synthetic MRI and CT images, which help augment datasets. Images generated by GANs can enhance the performance of image recognition models in radiology, especially in detecting rare conditions.

Drug Discovery: Generative AI is making significant progress in the field of drug discovery and design. Models such as Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) are capable of generating new molecular structures by learning from existing libraries of chemical compounds. This approach can greatly reduce the time and costs involved in identifying potential drug candidates. A study showed that deep generative models can efficiently explore chemical spaces, thereby accelerating the drug discovery process.

Personalized Medicine: Generative models are utilized to create personalized treatment simulations by developing predictive models of disease progression based on individual patient data. Research indicates that AI-generated simulations hold promise for predicting how individual patients will respond to cancer therapies. This approach can help in the creation of more effective, tailored treatment plans for patients.

Data Augmentation and De-biasing: Generative AI can enhance clinical datasets, especially for rare diseases where data is limited. Generative Adversarial Networks (GANs) can be used to create synthetic patient data to help balance datasets. This approach addresses bias in training data and improves the generalizability of machine learning models.

2. REVIEW OF LITERATURE

A literature review presents a comprehensive overview of the growing application of generative models, including Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Large Language Models (LLMs) across various healthcare domains. Many studies focus on leveraging generative models for drug response prediction and personalized treatment. For example, Rampašek et al. (2019) introduced DR. VAE, which outperforms standard classification methods in predicting the drug response for 23 out of 26 tested FDA-approved drugs. Similarly, Ge et al. (2020) demonstrated the power of Modified Conditional Generative Adversarial Networks (MCGANs) in estimating individualized treatment effects, outperforming seven other methods in the context of acute myeloid leukemia (AML) patients. However, the models' application is often limited to specific diseases or datasets. In a related area, Xue et al. (2020) employed Deep Generative Models (DGMs) to model cellular responses to drug perturbations, revealing crucial relationships between drugs and target genes, though their scalability for large, complex datasets remains a challenge. Additionally, Elazab et al. (2020) and Strack et al. (2023) demonstrated the use of stacked 3D GANs and Wasserstein GANs (WGANs), respectively, in predicting brain tumor growth and detecting tumor changes using longitudinal patient data. These studies underscore the ability of generative models to model disease progression over time and improve clinical decision-making.

Generative models are also crucial in addressing the challenges of data synthesis and privacy in healthcare. Yoon et al. (2020) applied ADS-GAN for anonymizing sensitive healthcare data, offering a reliable method for data generation with reduced re-identifiability. Similarly, Piacentino et al. (2021) demonstrated the use of GANs to generate synthetic ECGs for data anonymization, though this work is limited to ECG data without extensive testing on other healthcare data types. Jahanyar et al. (2023) used MS-ACGAN for data augmentation based on gene expression, producing data that closely mimics the original characteristics, though its application is confined to gene expression data. The growing trend of multi-omics data integration is explored in studies like Wang et al. (2023) and Ahmed et al. (2022), which employ generative models to integrate multi-omics data, improving the prediction of cancer outcomes and survival rates. Wang et al. (2023), for instance, used Multi-Omics Integrated Collective Variational Autoencoders (MOICVAE), achieving high AUC scores on several cancer datasets, but generalization across all cancer types remains uncertain.

The ability to generate counterfactual explanations and interpret treatment decisions is another key feature of generative models. Zhou et al. (2023) introduced SCGAN, which generates sparse counterfactual instances for breast cancer predictions, helping identify causal relationships between features and treatment responses. However, this method can be computationally expensive, and generating realistic counterfactuals can be difficult when multiple features are modified simultaneously. Moreover, Gao et al. (2023) used the BrainStatTrans-GAN to model individualized brain atrophy in Alzheimer's disease, demonstrating effective disease diagnosis and interpretation using MRI data from 1,739 subjects. While promising, its applicability to other brain diseases or patient groups is uncertain.

In the realm of clinical decision-making, studies like Benary et al. (2023) show the use of LLMs like Chat GPT for assisting oncology decisions, but the model's lack of credibility and low performance metrics, such as an F1 score of 0.29, limit its practical use. Similarly, Zhu et al. (2023) explored the use of GANs for generating personalized glucose time series in type 1 diabetes, reducing prediction error, but noted challenges in acquiring large-scale individual data due to privacy regulations. Rafael-Palou et al. (2022) also utilized generative models to predict tumor growth, demonstrating impressive accuracy in tumor size prediction but lacking direct comparisons with real-world clinical decisions.

Several studies have also employed generative models for missing data imputation and phenotype identification. Bernardini et al. (2023) introduced CCGAN, achieving notable improvements in imputation accuracy for electronic health records (EHRs), although performance can be affected by the rate of missing data and dataset heterogeneity. Similarly, Ahuja et al. (2022) applied a multi-modal Bayesian topic model for automatic phenotyping using EHR data, showing improvements in phenotype identification and comorbidity analysis, though it may not cover all phenotypes or datasets. Li et al. (2023) focused on a Network-based Generative Adversarial Semi supervised method, achieving high AUC scores for clinical prediction, yet model stability could be compromised with small labelled datasets.

Finally, Hsu and Lin (2023) used a Bayesian VAE to classify cancer prognosis from small datasets, achieving strong AUROC scores for breast cancer and non-small cell lung cancer (NSCLC), though the model's generalization in real-world clinical settings requires larger datasets for more reliable performance. Toufique et al. (2023) highlighted the use of LLMs for gene prioritization, but these models still face challenges in ensuring the accuracy and relevance of selected genes due to a lack of contextual understanding.

3. CHALLENGES AND OPPORTUNITIES

Generalizability Across Diverse Healthcare Contexts: Many studies show strong results in specific healthcare applications (e.g., glioma prediction, drug sensitivity modeling), but their generalizability across different disease types or patient cohorts remains limited. This is particularly notable in studies like Ge et al. (2020) and Rampašek et al. (2019), which focus on narrow datasets (e.g., acute myeloid leukemia, specific FDA drugs). Expanding these models to include diverse disease types and broader patient populations could improve their robustness. Research on model transferability across conditions (e.g., from glioma to breast cancer or from drug sensitivity to other medical contexts) could enhance the applicability of generative models.

Scalability to Large-Scale Datasets: Some models, such as Xue et al. (2020) and Ahmed et al. (2022), struggle with scalability, particularly when dealing with large datasets or complex perturbation profiles. This issue limits their ability to handle the full diversity of real-world healthcare data. There is a need for further research into the scalability of generative models, particularly focusing on the development of architectures that can handle multi-omics data and large clinical datasets without losing performance. This includes improving model efficiency and reducing computational demands.

Interpretability and Trust in Model Outputs: Despite high performance in generating predictions, many models lack sufficient interpretability (e.g., Zhou et al. (2023) with SCGANs and Benary et al. (2023) with LLMs). This leads to challenges in ensuring that healthcare practitioners can trust and act on these outputs in clinical settings. Research should focus on improving the explainability of generative models, particularly in the context of healthcare. Models like SCGAN and LLMs need better transparency in how predictions are made, which would foster trust among healthcare providers and patients. Developing interpretability methods that allow users to understand why a particular prediction or suggestion was made would be highly valuable.

Handling Missing Data and Anonymization: While some studies (e.g., Piacentino et al. (2021) and Bernardini et al. (2023)) focus on synthetic data generation and anonymization, challenges remain in fully ensuring privacy and addressing missing data across varied datasets. Privacy concerns also persist in healthcare due to the sensitive nature of patient information. More robust and universally applicable data anonymization techniques are required, particularly to ensure the ethical use of generative models. Research could also focus on methods for more accurate imputation of missing clinical data across diverse datasets with varying missingness patterns.

Bias and Fairness in Generative Models: While not explicitly discussed in the reviewed studies, generative models, especially those using large language models (e.g., Benary et al. (2023), Toufiq et al. (2023)), can unintentionally introduce or exacerbate biases present in the training data. This can affect clinical decision-making and outcomes. There is a significant need for research on bias detection and mitigation strategies in healthcare-related generative models. Ensuring fairness and equitable predictions across different demographic groups (e.g., race, gender, socioeconomic status) should be a key focus of future studies, particularly to avoid exacerbating health disparities.

Multi-modal Data Integration: Many studies, such as Gao et al. (2023) and M. Shi et al. (2023), demonstrate the potential of integrating multi-modal data (e.g., imaging, genomic, and clinical data), but these models often face challenges in truly integrating these different data types in a unified framework that produces reliable and actionable insights. Future research should develop better methods for seamlessly combining data from different modalities, ensuring that the strengths of each data type are fully leveraged while avoiding information loss or incompatibility between modalities.

Longitudinal Data and Personalized Medicine: Studies like Elazab et al. (2020) and Strack et al. (2023) focus on modeling disease progression using longitudinal data. However, their performance is often limited by dataset size or the need for better personalization of predictions. Research could focus on enhancing the use of longitudinal data for personalized medicine, specifically creating models that can predict disease progression on an individual level. This could help tailor treatments and improve patient outcomes in personalized healthcare settings.

Clinical Adoption and Integration: Despite promising results, the integration of generative models into real-world clinical practice remains a challenge. Models like ChatGPT-based decision support systems (e.g., Benary et al. 2023) show the potential of AI, but their utility is limited by the need for larger datasets, regulatory compliance, and adoption by healthcare providers. There is a gap in understanding the real-world barriers to the clinical adoption of generative models. Research could explore how these models can be effectively integrated into clinical workflows and how healthcare systems can adapt to leverage AI in decision-making while addressing ethical, regulatory, and usability concerns.

Robustness and Validation in Clinical Environments: Many generative models have been evaluated in controlled settings, but their robustness and validation in real-world clinical environments remain underexplored. Models like Zhu et al. (2023) and Moon et al. (2023) have shown promising results, but performance may vary when applied to larger and more diverse patient populations. Future studies should focus on validating generative models in real-world clinical settings, across diverse patient populations, and over extended periods. This would help determine their practical utility and identify any performance degradation in real-life scenarios.

4. CONCLUSION

This review examines studies from various databases that focus on the impact of artificial intelligence (AI) on precision medicine and the applications of synthetic data generation. In particular, Generative Adversarial Networks (GANs) have enhanced synthetic data generation, improving both accuracy and privacy. However, there are limitations, especially regarding the accuracy of foundation models like Large Language Models (LLMs) in digital diagnostics. The review identifies the uses, advantages, and challenges of generative AI (GAI) in healthcare. It underscores the importance of addressing GAI's limitations while providing a comprehensive overview of its potential to transform the healthcare landscape. Overcoming data scarcity and ensuring the generation of realistic, privacy-safe synthetic data are crucial for advancing personalized medicine. Additionally, further development of LLMs is essential for improving diagnostic precision. The application of generative AI in personalized medicine is on the rise, highlighting the need for more interdisciplinary research to advance this field.

REFERENCES

Ahuja Y, Zou Y, Verma A, Buckeridge D, Li Y (2022) MixEHR-Guided: A guided multi-modal topic modelling approach for large-scale automatic phenotyping using the electronic health record. J Biomed Inform, 134. https:// doi. org/ 10. 1016/j. jbi. 2022. 104190

Ahmed KT, Sun J, Cheng S, Yong J, Zhang W (2022) Multi-omics data integration by generative adversarial network. Bioinformatics 38(1):179–186. https:// doi. org/ 10. 1093/ bioin forma tics/ btab6 08

Barbiero P, Vinas Torne R, Lio P (2021) Graph Representation Forecasting of Patient’s Medical Conditions: Toward a Digital Twin. Front Gen, 12. https:// doi. org/ 10. 3389/ fgene. 2021. 652907

Benary M, Wang XD, Schmidt M, Soll D, Hilfenhaus G, Nassir M, Sigler C, Knodler M, Keller U, Beule D, Keilholz U, Leser U, Rieke DT (2023) Leveraging Large Language Models for Decision Support in Personalized Oncology. JAMA Netw Open 6(11):e2343689. https:// doi. org/ 10. 1001/ jaman etwor kopen.2023. 43689

Bernardini M, Doinychko A, Romeo L, Frontoni E, Amini MR (2023) A novel missing data imputation approach based on clinical conditional Generative Adversarial Networks applied to EHR datasets. Comput Biol Med, 163. https:// doi. org/ 10. 1016/j. compb iomed. 2023. 107188

El Emam K (2023) Status of Synthetic Data Generation for Structured Health Data. JCO Clinical Cancer Informatics, 7. https:// doi. org/ 10. 1200/ cci. 23. 00071

Elazab A, Wang C, Gardezi SJS, Bai H, Hu Q, Wang T, Chang C, Lei B (2020) GP-GAN: Brain tumor growth prediction using stacked 3D generative adversarial networks from longitudinal MR Images. Neural Netw 132:321–332. https:// doi. org/ 10. 1016/j. neunet. 2020. 09. 004

Gao X, Liu H, Shi F, Shen D, Liu M (2023) Brain Status Transferring Generative Adversarial Network for Decoding Individualized Atrophy in Alzheimer’s Disease. IEEE J Biomed Health Inform 27(10):4961–4970. https:// doi. org/ 10. 1109/ JBHI. 2023. 33043 88

Ge Q, Huang X, Fang S, Guo S, Liu Y, Lin W, Xiong M (2020) Conditional Generative Adversarial Networks for Individualized Treatment Effect Estimation and Treatment Selection. Front Gen, 11. https://doi. org/ 10. 3389/ fgene. 2020. 585804

Huang Y, Gomaa A, Semrau S, Haderlein M, Lettmaier S, Weissmann T, Grigo J, Ben TH, Frey B, Gaipl U, Distel L, Maier A, Fietkau R, Bert C, Putz F (2023) Benchmarking ChatGPT-4 on a radiation oncology in-training exam and Red Journal Gray Zone cases: potentials and challenges for ai-assisted medical education and decision making in adiation oncology. Front Oncol, 13. https:// doi. org/ 10. 3389/fonc. 2023. 12650 24

Hsu TC, Lin C (2023) Learning from small medical data - Robust semi-supervised cancer prognosis classifier with Bayesian variational autoencoder. Bioinform Adv, 3(1). https:// doi. org/ 10. 1093/ bioadv/ vbac100

Jahanyar B, Tabatabaee H, Rowhanimanesh A (2023) MS-ACGAN: A modified auxiliary classifier generative adversarial network for schizophrenia’s samples augmentation based on microarray gene expression data. Comput Biol Med, 162. https:// doi. org/ 10. 1016/j. compb iomed. 2023. 107024

Li R, Tian Y, Shen Z, Li J, Li J, Ding K, Li J (2023) Improving an Electronic Health Record–Based Clinical Prediction Model Under Label Deficiency: Network-Based Generative Adversarial Semisupervised Approach. JMIR Med Inform, 11. https:// doi. org/ 10. 2196/ 47862

Moon S, Lee Y, Hwang J, Kim CG, Kim JW, Yoon WT, Kim JH (2023) Prediction of anti-vascular endothelial growth factor agent-specific treatment outcomes in neovascular age-related macular degeneration using a generative adversarial network. Scientific Reports, 13(1). https:// doi. org/ 10. 1038/s41598- 023- 32398-7

Piacentino E, Guarner A, Angulo C (2021) Generating synthetic ecgs using gans for anonymizing healthcare data. Electronics (switzerland) 10(4):1–21. https:// doi. org/ 10. 3390/ elect ronic s1004 0389

Rafael-Palou X, Aubanell A, Ceresa M, Ribas V, Piella G, Ballester MAG (2022) Prediction of Lung Nodule Progression with an Uncertainty-Aware Hierarchical Probabilistic Network. Diagnostics, 12(11). https:// doi. org/ 10. 3390/ diagn ostic s1211 2639

Rampašek L, Hidru D, Smirnov P, Haibe-Kains B, Goldenberg A (2019) Dr.VAE: Improving drug response prediction via modeling of drug perturbation effects. Bioinformatics, 35(19), 3743–3751. https:// doi. org/ 10. 1093/ bioin forma tics/ btz158

Shi R, Sheng C, Jin S, Zhang Q, Zhang S, Zhang L, Ding C, Wang L, Wang L, Han Y, Jiang J (2023b) Generative adversarial network constrained multiple loss autoencoder: A deep learning-based individual atrophy detection for Alzheimer's disease and mild cognitive impairment. Hum Brain Mapp 44(3):1129–1146. https:// doi. org/ 10. 1002/ hbm. 26146

Shi M, Li X, Li M, Si Y (2023) Attention-based generative adversarial networks improve prognostic outcome prediction of cancer from multimodal data. Briefings in Bioinformatics, 24(6). https:// doi.org/ 10. 1093/ bib/ bbad3 29

Strack C, Pomykala KL, Schlemmer HP, Egger J, Kleesiek J (2023) A net for everyone: fully personalized and nsupervised neural networks trained with longitudinal data from a single patient. BMC Medical Imaging, 23(1). https:// doi. org/ 10. 1186/ s12880- 023- 01128-w

Sui D, Guo M, Ma X, Baptiste J, Zhang L (2021) Imaging Biomarkers and Gene Expression Data Correlation Framework for Lung Cancer Radiogenomics Analysis Based on Deep Learning. IEEE Access 9:125247–125257. https:// doi. org/ 10. 1109/ ACCESS. 2021. 30714 66

Tang Y, Zhang J, He D, Miao W, Liu W, Li Y, Lu G, Wu F, Wang S (2021) GANDA: A deep generative adversarial network conditionally generates intratumoral nanoparticles distribution pixels-to-pixels. J Control Release 336:336–343. https:// doi. org/ 10. 1016/j. jconr el. 2021. 06. 039

Toufiq M, Rinchai D, Bettacchioli E, Kabeer BSA, Khan T, Subba B, White O, Yurieva M, George J, Jourde-Chiche N, Chiche L, Palucka K, Chaussabel D (2023) Harnessing large language models (LLMs) for candidate gene prioritization and selection. J Translation Med, 21(1). https:// doi. org/ 10.1186/ s12967- 023- 04576-8

Wang C, Zhang M, Zhao J, Li B, Xiao X, Zhang Y (2023) The prediction of drug sensitivity by multi-omics fusion reveals the heterogeneity of drug response in pan-cancer. Comput Biol Med, 163. https:// doi.org/ 10. 1016/j. compb iomed. 2023. 107220

Xue Y, Ding MQ, Lu X (2020) Learning to encode cellular responses to systematic perturbations with deep generative models. NPJ Syst Biol Appl 6(1):35. https:// doi. org/ 10. 1038/ s41540- 020- 00158-2

Yamanaka C, Uki S, Kaitoh K, Iwata M, Yamanishi Y (2023) De novo drug design based on patient gene expression profiles via deep learning. Mol Inform, 42(8–9). https:// doi. org/ 10. 1002/ minf. 20230 0064

Yoon J, Drumright LN, Van Der Schaar M (2020) Anonymization through data synthesis using generative adversarial networks (ADS-GAN). IEEE J Biomed Health Inform 24(8):2378–2388. https:// doi. org/ 10.1109/ JBHI. 2020. 29802 62

Zhou S, Islam UJ, Pfeiffer N, Banerjee I, Patel BK, Iquebal AS (2023) SCGAN: Sparse CounterGAN for Counterfactual Explanations in Breast Cancer Prediction. IEEE Trans Autom Sci Eng, 1–12. https://doi. org/ 10. 1109/ TASE. 2023. 33337 88

Zhu T, Li K, Herrero P, Georgiou P (2023) GluGAN: Generating Personalized Glucose Time Series Using Generative Adversarial Networks. IEEE J Biomed Health Inform 27(10):5122–5133. https:// doi. org/10. 1109/ JBHI. 2023. 32716 15