

Large AI Models in Life Sciences and Healthcare: A Review and Analysis

Boyuan Fang

*Xi'an Shaangu High School, Xi'an, China
fby666666@icloud.com*

Abstract. Recent advances in large artificial intelligence (AI) models have transformed the landscape of life sciences and healthcare by enabling more efficient knowledge extraction, biomedical data analysis, and clinical decision support. Compared with traditional task-specific AI models, large language models (LLMs), generative AI, and multimodal foundation models demonstrate superior capabilities in knowledge representation, reasoning, and cross-domain learning. This review summarizes recent developments in the application of large AI models in life sciences and healthcare. First, the technical foundations of large AI models and their adaptation to biomedical data are introduced. Subsequently, representative applications in life science research, clinical healthcare, and drug discovery are reviewed, with particular attention to biomedical literature analysis, biological sequence modeling, medical image interpretation, clinical decision support, and precision medicine. Furthermore, the opportunities and challenges associated with deploying large AI models in healthcare are discussed, including improvements in research efficiency, disease diagnosis, and personalized treatment, as well as concerns regarding hallucination, privacy protection, algorithmic bias, interpretability, and regulatory governance. Overall, large AI models are reshaping biomedical research and healthcare delivery by promoting more intelligent, data-driven, and integrated approaches. Future progress will depend on continuous advances in trustworthy AI, multimodal learning, and interdisciplinary collaboration to ensure safe, reliable and clinically applicable AI systems.

Keywords: Large AI Models, Life Sciences, Healthcare, Large Language Models, Precision Medicine

1. Introduction

Artificial intelligence (AI) has become one of the most influential technologies driving innovation in life sciences and healthcare. With the rapid development of large language models (LLMs), generative AI, and multimodal foundation models, AI has evolved from task-specific prediction systems into general-purpose models capable of understanding, generating, and reasoning across diverse biomedical information. These advances provide new opportunities for addressing complex challenges in disease diagnosis, biomedical research and drug discovery.

Meanwhile, life sciences and healthcare continuously generate enormous amounts of heterogeneous data, including biomedical literature, electronic health records (EHRs), medical

images, genomic data, and multi-omics datasets. The complexity, high dimensionality, and multimodal characteristics of these data often exceed the capabilities of conventional machine learning methods, making efficient knowledge integration and clinical interpretation increasingly difficult. Large AI models offer a promising solution by learning general knowledge from large-scale datasets and adapting it to specialized biomedical tasks through domain-specific training strategies.

This paper aims to summarize recent progress in applying large AI models to life sciences and healthcare. It first introduces the technical foundations of these models and their adaptation to biomedical data. It then reviews representative applications in life science research, clinical healthcare, and drug discovery. Finally, it discusses the major opportunities and challenges associated with the deployment of large AI models, including reliability, privacy protection, ethical considerations and regulatory governance. By reviewing current research, this paper provides a comprehensive overview of how large AI models are advancing biomedical science and healthcare while highlighting future research directions.

2. Technical foundations of large AI models for life sciences and healthcare

2.1. Large AI models: concepts and technical foundations

Large AI models have consistently become a significant milestone in the evolution of artificial intelligence. Unlike conventional machine learning models that are designed for specific tasks, large AI models are pretrained on massive datasets and can be adapted to various downstream applications. Large language models (LLMs), generative AI, and multimodal foundation models are representative examples of this paradigm. Their ability to learn generalized knowledge and perform complex reasoning has substantially improved the processing of biomedical information. Recent evidence suggests that these models provide a unified framework for understanding scientific literature, generating medical content, and supporting clinical decision-making, making them increasingly valuable for life sciences and healthcare research [1, 2].

The rapid progress of large AI models is mainly driven by the Transformer architecture and the pretraining–fine-tuning paradigm. The self-attention mechanism enables models to capture long-range contextual relationships efficiently, while large-scale pretraining allows them to acquire extensive linguistic and scientific knowledge. Through domain-specific fine-tuning or instruction tuning, these models can effectively perform specialized biomedical tasks with relatively limited annotated data. Consequently, large AI models have become more adaptable and scalable than traditional task-specific AI systems [2, 3].

2.2. Biomedical data characteristics and domain adaptation

Life sciences and healthcare involve highly heterogeneous data, including biomedical literature, electronic health records (EHRs), medical images, biological sequences, and multi-omics datasets. These data differ in format, scale, and semantic representation, posing significant challenges for conventional AI methods. Large AI models address these challenges by learning shared representations across multiple data modalities, thereby facilitating knowledge integration and improving analytical performance. This capability is particularly important for precision medicine, where clinical decisions often rely on the comprehensive interpretation of heterogeneous biomedical information [3, 4].

To further improve domain-specific performance, general-purpose large AI models are commonly adapted using biomedical pretraining, retrieval-augmented generation (RAG), and multimodal learning techniques. These approaches enhance factual accuracy, strengthen biomedical knowledge representation, and reduce hallucination in medical applications. Despite their considerable advantages in scalability, reasoning, and cross-modal learning, challenges such as computational cost, interpretability, privacy protection, and regulatory compliance remain important barriers to the widespread adoption of large AI models in life sciences and healthcare [1-5].

3. Applications of large AI models in life sciences and healthcare

3.1. Applications in life science research

Large AI models have consistently significantly expanded the capabilities of life science research by improving knowledge discovery, biological data analysis, and scientific reasoning. Traditional biomedical research often requires researchers to manually analyze extensive scientific literature and integrate evidence from multiple experimental studies. This process is time-consuming and may overlook valuable information due to the rapid growth of biomedical publications. Large language models provide an effective solution by automatically summarizing scientific literature, extracting biomedical entities and relationships, and identifying potential research trends. These capabilities greatly improve research efficiency and support evidence-based scientific discovery [1, 2].

Another important application is biological sequence modeling. Inspired by natural language processing, researchers have treated DNA, RNA, and protein sequences as biological "languages." Large AI models trained on massive biological sequence databases are capable of learning sequence patterns, predicting protein structures and functions, identifying functional mutations, and analyzing gene regulation. Such models provide valuable computational tools for understanding disease mechanisms and accelerating biological discoveries, particularly in genomics and molecular biology [3].

Moreover, large AI models also facilitate the integration of multi-omics data, including genomics, transcriptomics, proteomics, metabolomics, and epigenomics. These datasets describe biological systems from different molecular perspectives and often contain complementary information. Conventional analytical methods usually process each omics dataset separately, making comprehensive interpretation difficult. By contrast, multimodal large AI models can integrate heterogeneous biological data into unified representations, enabling more accurate disease classification, biomarker discovery, and personalized risk prediction. This capability supports precision medicine by providing a more comprehensive understanding of complex biological processes [3, 4].

Overall, recent studies indicate that large AI models are transforming life science research from data-intensive analysis toward knowledge-driven discovery. Rather than serving merely as computational tools, these models increasingly function as intelligent research assistants capable of supporting hypothesis generation, knowledge integration, and scientific decision-making [2, 4].

In addition to knowledge extraction, large AI models are increasingly being used to support scientific reasoning and interdisciplinary research. By integrating information from biomedical publications, clinical databases, and public biological repositories, these models can identify potential associations between genes, diseases, and therapeutic targets that may not be immediately apparent through conventional literature review. Such capabilities help researchers generate new hypotheses, prioritize experimental directions, and reduce the time required for early-stage scientific exploration. Although AI-generated hypotheses still require experimental validation, they provide an

efficient starting point for biomedical discovery and facilitate collaboration between computational scientists and experimental researchers [2, 4].

3.2. Applications in clinical healthcare

Large AI models have consistently demonstrated considerable potential in clinical healthcare by supporting disease diagnosis, medical documentation, and clinical decision-making. One of the most widely studied applications is the processing of electronic health records (EHRs). Clinical records contain large volumes of unstructured text, including physicians' notes, discharge summaries, laboratory reports, and treatment histories. Large language models can efficiently extract key clinical information, summarize patient records, and identify potential disease risks, thereby reducing clinicians' administrative workload and improving healthcare efficiency [1, 5].

Medical imaging is another important application area. Recent multimodal foundation models combine imaging data with clinical text to improve the interpretation of computed tomography (CT), magnetic resonance imaging (MRI), X-ray images, and digital pathology. Compared with conventional image classification models, multimodal approaches provide more comprehensive clinical information by integrating visual features with patient history and diagnostic reports. Consequently, they have shown promising performance in lesion detection, disease classification, and prognosis assessment [3, 6].

Moreover, large AI models also contribute to clinical decision support by retrieving medical knowledge, interpreting clinical guidelines, and generating evidence-based recommendations. Rather than replacing physicians, these systems function as intelligent assistants that provide timely information and facilitate more informed clinical decisions. Nevertheless, current research emphasizes that AI-generated recommendations should always be verified by healthcare professionals because model hallucination and factual inaccuracies remain potential risks in high-stakes medical environments [1, 2].

Another promising application involves patient communication and healthcare management. Large AI models can effectively provide understandable explanations of medical terminology, generate personalized health education materials, and assist patients in managing chronic diseases through intelligent dialogue systems. These applications may improve patient engagement and health literacy while reducing the workload of healthcare providers. Nevertheless, AI-generated medical information should always be reviewed by qualified professionals to ensure accuracy and prevent potential misunderstandings that could affect patient safety [1, 5].

3.3. Applications in drug discovery and precision medicine

Drug discovery is a complex and time-consuming process that requires substantial financial investment and extensive experimental validation. Large AI models have consistently emerged as valuable tools for accelerating different stages of drug development. By learning from large-scale biomedical literature, chemical databases, and molecular structures, these models can identify potential therapeutic targets, predict drug–target interactions, and generate candidate molecules with desired properties. Compared with traditional computational approaches, large AI models improve screening efficiency and reduce the time required for early-stage drug discovery [3, 7].

Moreover, large AI models also play an important role in precision medicine. By integrating genomic information, clinical records, medical images, and other patient-specific data, these models can support disease risk prediction, patient stratification, and individualized treatment planning. Such data-driven approaches enable clinicians to develop more personalized therapeutic strategies

based on the biological characteristics of each patient. In addition, generative AI has shown considerable potential in drug repurposing by identifying new therapeutic applications for existing drugs, thereby reducing development costs and shortening the time needed for clinical translation [4, 7].

Despite these promising advances, most AI-assisted drug discovery systems remain in the research or early clinical validation stage. Further improvements in model reliability, experimental verification, and interdisciplinary collaboration will be essential before large AI models can be widely adopted in pharmaceutical research and precision medicine [2, 3].

Furthermore, the integration of large AI models with laboratory automation and high-throughput screening technologies is expected to further accelerate pharmaceutical innovation. By combining computational prediction with experimental validation, researchers can establish more efficient drug development pipelines that shorten the transition from basic research to clinical application. Although practical implementation remains limited, this interdisciplinary approach represents an important direction for future biomedical research and precision medicine [3, 7].

4. Opportunities and challenges

4.1. Opportunities

The integration of large AI models into life sciences and healthcare has created unprecedented opportunities for both scientific research and clinical practice. By processing heterogeneous biomedical data, these models facilitate knowledge discovery, improve research efficiency, and accelerate the translation of scientific findings into clinical applications. In healthcare, large AI models support physicians by enhancing diagnostic accuracy, reducing administrative burdens, and enabling more personalized treatment recommendations. Their ability to integrate medical images, clinical records, and genomic information also promotes the development of precision medicine, allowing treatment strategies to be tailored to individual patient characteristics [1, 3].

Beyond clinical applications, large AI models have become valuable research assistants capable of summarizing scientific evidence, generating research hypotheses, and identifying potential relationships hidden within massive biomedical datasets. As multimodal foundation models continue to evolve, they are expected to further strengthen interdisciplinary collaboration among computer science, biology, and medicine, thereby promoting innovation throughout the biomedical research ecosystem [2, 4].

4.2. Challenges

Despite their promising performance, large AI models still face significant challenges before they can be safely deployed in real-world healthcare settings. One major concern is the generation of inaccurate or fabricated information, commonly referred to as hallucination, which may lead to inappropriate clinical recommendations if not carefully verified. Since medical decisions directly affect patient safety, AI-generated outputs must always be interpreted and validated by qualified healthcare professionals [1, 5].

Another important challenge involves data privacy and security. Large AI models require substantial amounts of biomedical data for training and optimization, raising concerns regarding patient confidentiality, informed consent, and compliance with healthcare regulations. In addition, biases within training datasets may reduce model fairness and limit their generalizability across different populations. The limited interpretability of deep learning models further affects clinicians'

trust and acceptance of AI-assisted decision-making. Therefore, future research should focus on improving model transparency, reliability, and regulatory governance while establishing ethical frameworks that ensure the responsible development and application of large AI models in life sciences and healthcare [2, 3, 8].

Another challenge concerns the transparency and explainability of large AI models. Clinical decisions often require clear evidence and logical justification, whereas many deep learning models operate as "black boxes." Improving model interpretability is therefore essential for increasing clinicians' confidence and facilitating regulatory approval. In addition, establishing standardized evaluation benchmarks and continuous post-deployment monitoring will be necessary to ensure the long-term safety and reliability of AI-assisted healthcare systems [2, 3, 9].

5. Conclusion

Large AI models have consistently rapidly become one of the most transformative technologies in life sciences and healthcare. Their strong capabilities in knowledge representation, multimodal learning, and complex reasoning have significantly expanded the scope of biomedical research and clinical applications. As reviewed in this paper, large AI models have demonstrated considerable potential in biomedical literature analysis, biological sequence modeling, multi-omics data integration, clinical decision support, medical image interpretation, drug discovery, and precision medicine. These advances have not only improved the efficiency of scientific research but have also contributed to more accurate disease diagnosis and personalized healthcare.

Despite these achievements, the widespread adoption of large AI models in healthcare still faces substantial challenges. Issues such as hallucination, limited interpretability, algorithmic bias, data privacy, and regulatory compliance continue to affect their reliability and clinical applicability. Since healthcare is a high-risk domain, AI systems should be regarded as decision-support tools rather than replacements for medical professionals. Human supervision, rigorous clinical validation, and evidence-based evaluation remain essential to ensure patient safety and public trust.

Looking ahead, future research should focus on developing trustworthy and domain-specific biomedical AI models with improved transparency, robustness, and multimodal reasoning capabilities. Greater collaboration among computer scientists, biomedical researchers, clinicians, and policymakers will also be necessary to establish effective ethical guidelines and regulatory frameworks. With continuous technological innovation and responsible governance, large AI models are expected to play an increasingly important role in advancing life sciences, accelerating biomedical discoveries, and improving global healthcare systems.

Continued collaboration between academia, industry, clinicians, and policymakers will be essential for translating these technological advances into safe, effective, and equitable healthcare solutions supported by robust clinical evidence [10-12].

References

- [1] Thirunavukarasu, A., Ting, D. S. J., Elangovan, K., Gutierrez, L., Tan, T. F., & Ting, D. S. W. (2023). Large language models in medicine. *Nat Med*, 29(8), 1930-1940.
- [2] Wang, D., & Zhang, S. (2024). Large language models in medical and healthcare fields: Applications, advances, and challenges. *Artif Intell Rev*, 57, 299.
- [3] Liu, F., Zhou, H., Gu, B., Zou, X., Huang, J., et al. (2025). Application of large language models in medicine. *Nat Rev Bioeng*, 3, 445-464.
- [4] Maity, S., & Saikia, M. J. (2025). Large language models in healthcare and medical applications: A review. *Bioengineering (Basel)*, 12(6), 631.

- [5] Al Nazi, Z., & Peng, W. (2024). Large language models in healthcare and medical domain: A review. *Informatics*, 11(3), 57.
- [6] Ryu, J. S., Kang, H., Chu, Y., et al. (2025). Vision-language foundation models for medical imaging: A review of current practices and innovations. *Biomed Eng Lett*, 15, 809-830.
- [7] Zheng, Y., Koh, H. Y., Yang, M., Li, L., May, L. T., Webb, G. I., et al. (2024). Large language models in drug discovery and development: From disease mechanisms to clinical trials. arXiv: 2409.04481.
- [8] Omiye, J. A., Gui, H., Rezaei, S. J., Zou, J., & Daneshjou, R. (2023). Large language models in medicine: The potentials and pitfalls. arXiv: 2309.00087.
- [9] Dorfner, F. J., Dada, A., Busch, F., Makowski, M. R., Han, T., Truhn, D., et al. (2024). Biomedical large language models seem not to be superior to generalist models on unseen medical data. arXiv: 2408.13833.
- [10] Buess, L., Keicher, M., Navab, N., Maier, A., & Arasteh, S. T. (2025). From large language models to multimodal AI: A scoping review on the potential of generative AI in medicine. arXiv: 2502.09242.
- [11] Topol, E. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nat Med*, 25(1), 44–56.
- [12] Zhou, J., Li, H., Chen, S., Chen, Z., Han, Z., & Gao, X. (2025). Large language models in biomedicine and healthcare. *npj Artif Intell*, 1, 47.