

## Integrating Artificial Intelligence, Machine Learning, and Molecular Sciences in Biomedical Research: Applications in Laboratory Medicine, Cancer Biology, and Public Health

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**Abstract:** Artificial intelligence (AI) and machine learning (ML) are rapidly transforming biomedical research, offering novel solutions to longstanding challenges in laboratory medicine, cancer biology, molecular sciences, drug discovery, and public health. These technologies enable the analysis of vast, complex datasets, facilitating pattern recognition, predictive modeling, and data integration at scales beyond human capability. In laboratory medicine, AI and ML enhance diagnostic accuracy, automate repetitive processes, reduce errors, and shorten turnaround times, while supporting decision-making through intelligent data interpretation. In cancer biology, machine learning models integrate genomic, proteomic, imaging, and clinical data to predict disease progression, therapeutic response, and patient outcomes, advancing precision oncology. Similarly, AI applications in molecular sciences, including molecular pathology and allergen classification, improve disease categorization and personalized treatment strategies. In drug discovery, AI accelerates compound screening, predicts drug-target interactions, and supports rational design of therapeutics, exemplified by technologies such as AlphaFold, which accurately models protein structures. Public health also benefits from AI-driven predictive modeling for outbreak detection, risk stratification, and resource optimization. Despite these advancements, challenges remain, including the need for high-quality, representative datasets, algorithm validation, ethical considerations, data privacy, and workforce training. Interdisciplinary collaboration among clinicians, researchers, data scientists, and policymakers is essential to ensure responsible and effective implementation. Looking forward, AI and ML are poised to redefine biomedical research, enabling data-driven insights, personalized medicine, and improved healthcare outcomes, provided that technical, ethical, and regulatory challenges are addressed.

**Keywords:** Artificial Intelligence, Machine Learning, Biomedical Research, Precision Medicine, Laboratory Medicine

### Introduction

The integration of artificial intelligence and machine learning into biomedical research represents a fundamental shift in how health data are generated, analyzed, and used to inform clinical decision-making. Across laboratory medicine, cancer biology, and public health, AI and ML are redefining traditional research and diagnostic paradigms by enabling the rapid analysis of complex, high-dimensional biological datasets [1]. What this really means is a move away from purely manual, experience-driven interpretation toward data-informed, predictive, and increasingly personalized approaches to healthcare. In laboratory medicine, AI-driven systems are transforming both analytical and operational workflows. Machine learning algorithms can process vast volumes

of laboratory data to detect subtle patterns that may be missed by conventional statistical methods or human observation [2]. Deep learning models applied to histopathology, hematology, and clinical chemistry have demonstrated high accuracy in identifying abnormalities, classifying disease states, and supporting diagnostic decisions. Automation powered by AI also reduces human error, shortens turnaround time, and allows laboratory professionals to focus on complex interpretive tasks rather than repetitive processes [3]. As a result, laboratories are becoming more efficient while maintaining or improving diagnostic reliability. Cancer biology is another area where AI and ML have shown exceptional promise. Cancer is inherently complex, driven by interactions between genetic mutations, epigenetic regulation, tumor microenvironments, and host immune responses [4]. Machine learning models can integrate genomic, transcriptomic, proteomic, imaging, and clinical data to uncover relationships that are otherwise difficult to detect. These approaches are increasingly used to predict disease progression, stratify patients based on risk, and estimate responses to specific therapies. Models such as multi-modal AI frameworks developed by academic medical centers illustrate how diverse data streams can be combined to guide treatment planning [5]. This shift supports the broader goal of precision oncology, where therapeutic decisions are tailored to the biological and clinical characteristics of individual patients rather than generalized treatment protocols. Beyond individual patient care, AI and ML play a critical role in public health research and population-level disease management. Predictive modeling enables early detection of disease outbreaks, identification of high-risk populations, and optimization of resource allocation. Machine learning algorithms can analyze epidemiological data, environmental factors, and social determinants of health to forecast disease trends and inform preventive strategies [6]. During global health crises, such tools can support rapid decision-making by public health authorities, enhancing preparedness and response capabilities. Despite these advances, integrating AI and ML into biomedical research poses significant challenges that must be addressed to ensure responsible and equitable use. Data privacy and security remain central concerns, particularly when handling sensitive patient information [7]. Informed consent frameworks must evolve to account for secondary data use and algorithmic analysis. Algorithmic bias is another critical issue; models trained on non-representative or low-quality datasets may reinforce existing health disparities across gender, ethnicity, or socioeconomic groups. The reliability and interpretability of AI systems also require careful validation, as black-box models can undermine clinical trust and accountability [8]. Addressing these challenges requires strong interdisciplinary collaboration among biomedical scientists, clinicians, data scientists, ethicists, and policy makers. Transparent model development, rigorous validation, and continuous performance monitoring are essential for safe implementation. Equally important is the creation of diverse, high-quality datasets that reflect real-world populations. Initiatives such as large-scale national and international data sharing programs aim to support this goal by providing standardized, ethically sourced data resources for AI research [9]. Looking ahead, AI and ML are poised to become integral components of biomedical research rather than auxiliary tools. As computational methods continue to evolve and ethical frameworks mature, their impact on diagnostics, treatment planning, and disease prevention will expand. When implemented thoughtfully, AI-driven approaches can enhance diagnostic accuracy, improve patient outcomes, and strengthen public health systems in an increasingly data-driven healthcare landscape.

### **Artificial Intelligence and Machine Learning in Biomedical Research**

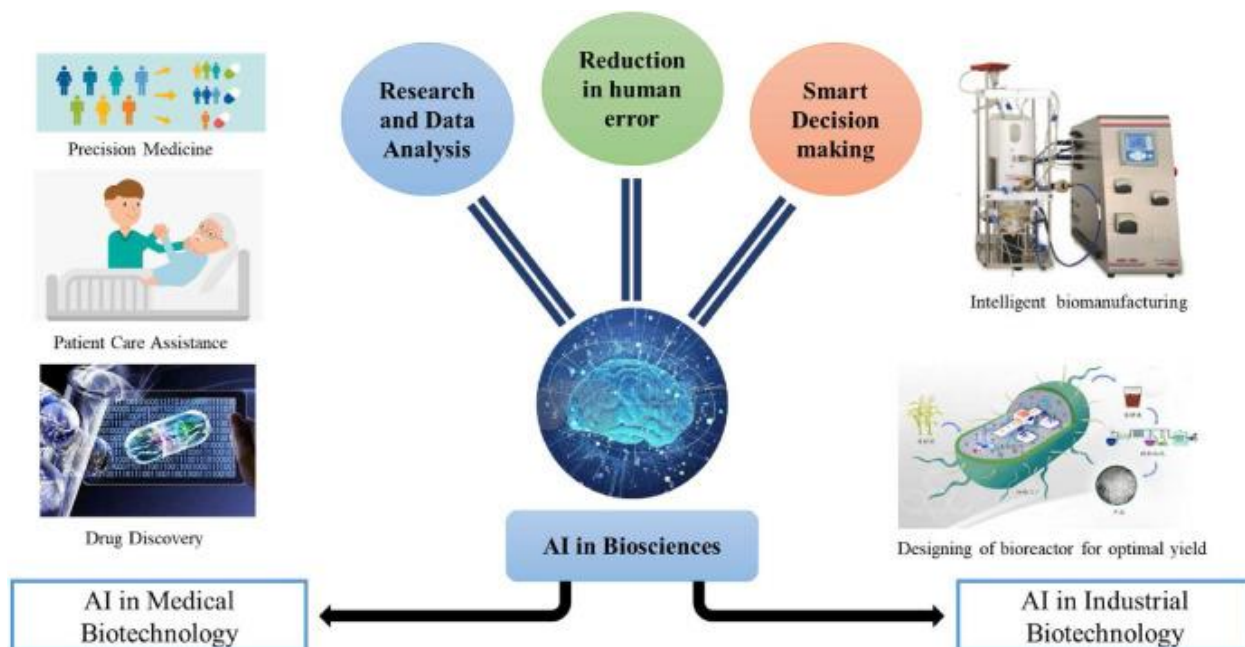
Artificial intelligence and machine learning are increasingly central to biomedical research, particularly in laboratory medicine, cancer biology, and public health. Their integration represents a clear shift from traditional, largely manual methodologies toward data-driven, automated, and predictive systems [10]. At its core, this transformation aims to improve diagnostic accuracy, optimize laboratory workflows, and support better clinical and public health decision-making, ultimately leading to improved patient outcomes. The development of AI in laboratory medicine is closely linked to the early adoption of computers and automated analytical instruments in clinical laboratories. Initial advances focused on automating routine analytical tasks, such as sample processing and result generation. Over time, these systems evolved into more sophisticated AI-

driven infrastructures that integrate analyzers, robotic sample handling, and laboratory information management systems [11]. Together, these components streamline the entire testing process, from patient registration and sample tracking to result validation and reporting. This evolution has laid the foundation for modern high-throughput, high-reliability laboratory services. One of the most significant advantages of AI integration in laboratory medicine is the automation of repetitive and time-consuming processes. By reducing manual intervention, AI systems increase efficiency, shorten turnaround times, and minimize human error. Beyond automation, AI algorithms excel at analyzing large and complex datasets, identifying patterns and anomalies that may not be apparent through conventional analysis [12]. This capability enhances diagnostic accuracy and enables predictive diagnostics, supporting early disease detection and risk stratification. AI also strengthens clinical decision support by integrating laboratory data with clinical, demographic, and, at times, imaging information, enabling healthcare professionals to make more informed, timely decisions (Figure 1) [13]. Additionally, AI plays a critical role in advancing personalized medicine by integrating multi-omics data, including genomics, proteomics, metabolomics, and transcriptomics, to tailor diagnostic and therapeutic approaches to individual patient profiles. In cancer biology, the application of AI and ML has been particularly impactful. Cancer is a biologically complex and heterogeneous disease, making it well-suited to data-intensive computational approaches. Advanced AI models can combine histopathological images, molecular data, and clinical records to predict disease prognosis and treatment response [14]. A notable example is the development of multimodal AI systems that integrate visual and text-based data to identify which patients are most likely to benefit from specific therapies. These approaches not only improve diagnostic precision but also optimize treatment pathways, supporting the broader goal of precision oncology. Machine learning, as a subset of AI, has further expanded the analytical capabilities of biomedical research (Table 1). Supervised and unsupervised learning methods are widely used to classify disease states, discover hidden data structures, and predict clinical outcomes [15]. In clinical laboratories, ML models are particularly effective in image-based analyses, such as identifying cellular abnormalities, bacterial colonies, or cancerous tissue. Deep learning networks have demonstrated performance comparable to, and in some cases exceeding, that of experienced pathologists, offering reliable decision support and valuable second opinions. Machine learning is also applied in natural language processing, where algorithms analyze unstructured clinical text to extract relevant information and predict treatment efficacy based on tumor characteristics and patient history [16]. Despite these advances, integrating AI and ML into biomedical research poses significant challenges. Ethical issues related to data privacy, informed consent, and algorithmic bias require careful consideration. The performance of AI systems is highly dependent on the quality and representativeness of training datasets, and biased data can reinforce existing health disparities. Addressing these concerns requires interdisciplinary collaboration among clinicians, researchers, data scientists, and ethicists, along with transparent model development and rigorous validation [17]. Overall, the combined application of artificial intelligence and machine learning is reshaping biomedical research and practice. When implemented responsibly, these technologies hold significant potential to enhance diagnostic accuracy, improve laboratory efficiency, personalize treatment strategies, and strengthen public health systems in an increasingly data-driven healthcare environment.

**Table 1.** Key Applications of Artificial Intelligence and Machine Learning in Biomedical Research.

Application Area	AI/ML Use Case	Key Contribution	Reference
Online Education	Virtual teaching assistants (e.g., Jill Watson)	Enhances student engagement and scalable instructional support	[48]
Laboratory Medicine	Diagnostic automation and decision support	Improves accuracy, reduces turnaround time and human error	[49]

Cancer Biology	Multi-omics data integration	Supports prognosis prediction and precision oncology	[2]
Drug Discovery	Protein structure prediction (AlphaFold)	Accelerates rational drug design and target identification	[29]
Public Health	Predictive modeling and surveillance	Enables outbreak prediction and resource optimization	[42]



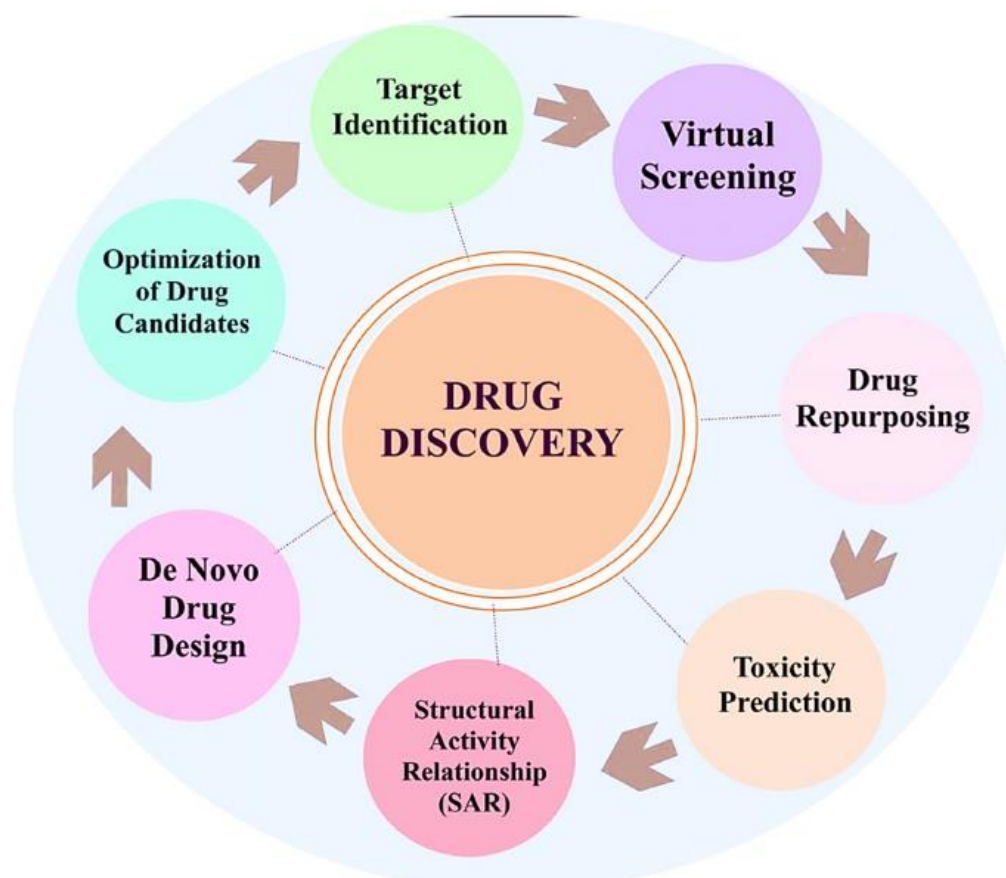
**Figure 1.** The application possibilities of artificial intelligence in the disciplines of health and industrial biotechnology [50].

### Future Directions, Innovations, and the Role of AI and Machine Learning in Molecular Biomedical Research

Machine learning and artificial intelligence are expected to play an even more decisive role in shaping the future of biomedical research. Large-scale initiatives such as the National Institutes of Health Bridge2AI program reflect a clear strategic shift toward building extensive, high-quality datasets explicitly designed for AI-driven discovery [18]. This movement signals a transition from purely hypothesis-driven research toward data-intensive, exploratory approaches that can generate actionable insights at both the individual and population levels. What this really means is that biomedical research is becoming increasingly predictive, adaptive, and responsive to real-world health challenges. At the molecular level, the integration of AI and ML has fundamentally changed how biological data is interpreted [19]. Modern biomedical research now routinely involves massive datasets derived from genomics, epigenomics, proteomics, transcriptomics, and metabolomics. Machine learning algorithms are uniquely suited to handle this complexity, allowing researchers to uncover hidden patterns, molecular signatures, and disease-associated pathways that would be difficult to detect using traditional analytical methods. The growing recognition that biology functions as an information-rich system underscores the importance of computational approaches for understanding disease mechanisms and therapeutic targets. In molecular pathology, AI and ML have demonstrated strong potential to improve diagnostic precision and disease classification [20]. One prominent application is the use of DNA methylation profiling combined with machine learning to classify central nervous system tumors with high accuracy. Similarly, digital pathology powered by deep learning enables automated image analysis of tissue sections, supporting more consistent and objective diagnoses [21]. These technologies are increasingly incorporated into laboratory medicine information systems, where they help predict laboratory test results, identify analytical errors, and optimize workflow efficiency. As



adoption grows, these tools are expected to reduce diagnostic variability and enhance overall laboratory performance [22]. Another innovative application of machine learning in molecular sciences is the classification of allergenic molecules (Figure 2). By analyzing large datasets of protein sequences and structural features, ML algorithms can predict allergenic potential, identify key amino acid compositions, and trace the sources of allergenicity [23]. This approach supports more precise allergy diagnostics and enables personalized treatment strategies, improving the clinical management of allergic diseases. Such applications highlight how AI-driven molecular analysis can translate directly into patient-specific care [24]. In clinical laboratory settings, the future impact of AI and ML lies in their ability to integrate and interpret diverse biological and clinical data in real time. Automated systems can manage repetitive laboratory tasks, reduce turnaround times, and enhance the accuracy of complex analyses. More importantly, AI-driven pattern recognition enables early disease detection by identifying subtle changes in laboratory results before clinical symptoms appear [25]. This predictive capability strengthens preventive medicine and supports earlier intervention, which is critical for improving long-term patient outcomes. Overall, future innovations in biomedical research will be driven by the convergence of AI, machine learning, and molecular sciences. As data infrastructures improve and ethical frameworks mature, these technologies will increasingly support precision diagnostics, personalized therapies, and efficient laboratory operations [26]. When combined with interdisciplinary collaboration and responsible data governance, AI and ML have the potential to redefine how diseases are understood, diagnosed, and managed in modern healthcare systems.



**Figure 2.** Future process of drug discovery with the help of AI [51].

### Challenges of AI and Machine Learning in Biomedical Research

Artificial intelligence and machine learning are driving major innovations across biomedical research, with a powerful impact on drug discovery, laboratory medicine, cancer biology, and public health. At the same time, their practical implementation depends on interdisciplinary collaboration and careful management of technical, ethical, and practical challenges [27]. Understanding these interconnected dimensions is essential for translating computational advances

into real clinical and public health benefits. One of the most transformative innovations enabled by AI is in drug discovery and pharmaceutical research. Traditional drug development is time-intensive, costly, and marked by high failure rates. AI-powered platforms can rapidly screen millions of chemical compounds, model drug target interactions, and predict toxicity and efficacy long before clinical testing begins [28]. This capability dramatically shortens development timelines and reduces research costs. A landmark example is AlphaFold, which accurately predicts protein structures that were previously difficult or impossible to resolve experimentally. By providing detailed insights into protein folding and interactions, such technologies are accelerating the design of novel therapeutics for complex conditions, including neurodegenerative diseases and inherited genetic disorders [29]. These advances signal a shift toward more rational, structure-based drug design guided by computational intelligence. Despite this progress, several challenges continue to limit the full potential of AI and ML in molecular sciences. High-quality, well-structured, and accurately labeled datasets remain a fundamental requirement for training reliable models. Inconsistent data standards across laboratories, variability in biomarker measurement, and limited availability of clinically validated datasets can compromise model performance [30]. Moreover, the clinical validation of AI algorithms is essential before routine adoption, as predictive accuracy in research settings does not always translate directly to the real world. Addressing these limitations is critical for ensuring that AI-driven tools are safe, reproducible, and clinically meaningful. The complexity of these challenges underscores the importance of interdisciplinary approaches in biomedical AI integration. Successful implementation requires collaboration among laboratory scientists, clinicians, bioinformaticians, data scientists, information technology specialists, and biostatisticians [31]. Each group contributes essential expertise, from understanding biological mechanisms and clinical needs to designing algorithms and managing data infrastructures. Collaborative development enables AI tools that are not only technically robust but also clinically relevant and user-centered. In public health, such partnerships are particularly valuable for standardizing data protocols and improving disease surveillance, risk prediction, and response strategies (Table 2) [32]. However, integrating AI into laboratory medicine and broader healthcare systems is not without obstacles. Beyond data quality issues, concerns persist regarding algorithm transparency, validation, data privacy, and ethical use of patient information. Black box models can erode clinician trust and complicate accountability, while inadequate data governance increases risks of confidentiality breaches and misuse. Establishing strict validation protocols, regulatory oversight, and international standards is therefore essential to ensure the reliability and responsible deployment of AI applications in clinical laboratories and healthcare settings [33]. Education and workforce development play a critical role in overcoming these integration challenges. Continuous training programs are necessary to keep laboratory professionals and clinicians informed about evolving AI technologies and analytical methods. Incorporating AI-related content into medical, laboratory science, and public health curricula can prepare future professionals to work confidently with these tools [34]. A workforce that understands both the capabilities and limitations of AI is more likely to adopt it effectively and safely. Looking forward, the continued integration of AI and ML into biomedical research holds substantial promise for improving diagnostic accuracy, accelerating drug development, and enhancing patient outcomes. Achieving this potential will require a balanced approach that combines technological innovation with interdisciplinary collaboration, rigorous validation, ethical governance, and sustained education [35]. By addressing current challenges and limitations, stakeholders can ensure that AI evolves as a trusted and transformative component of modern biomedical science and healthcare.

**Table 2.** Challenges and Ethical Considerations of AI Integration in Biomedical Research.

Challenge Area	Description	Impact on Healthcare	Reference
Data Privacy	Use of large-scale patient datasets	Risk of confidentiality breaches and misuse of health data	[43]
Algorithmic Bias	Non-representative training data	Reinforces health disparities and inequitable care	[49]

Interpretability	Black-box AI models	Reduces clinician trust and accountability	[3]
Education & Training	Limited AI literacy among clinicians	Slows adoption and effective implementation	[3], [49]
Regulatory Oversight	Lack of standardized validation frameworks	Limits clinical translation and scalability	[47]

## Discussion

The rapid integration of artificial intelligence (AI) and machine learning (ML) into biomedical research represents one of the most significant paradigm shifts in modern healthcare science. Across laboratory medicine, cancer biology, molecular sciences, drug discovery, and public health, these technologies are reshaping how data are generated, interpreted, and translated into clinical and population-level action [36]. This discussion critically examines the implications of AI and ML integration, highlighting their transformative potential, interdisciplinary requirements, ongoing challenges, and future directions within biomedical research. A central strength of AI and ML lies in their ability to process and learn from vast, complex, and multidimensional datasets that far exceed human analytical capacity [37]. Biomedical research increasingly relies on high-throughput technologies such as next-generation sequencing, advanced imaging, multi-omics profiling, and electronic health records. Traditional statistical methods, while valuable, often struggle to capture nonlinear relationships and hidden patterns within such data. AI and ML address this gap by enabling pattern recognition, predictive modeling, and data integration at unprecedented scales [38]. As a result, biomedical research is shifting from descriptive and hypothesis-limited approaches toward data-driven, predictive frameworks that can uncover novel biological insights and inform clinical decision-making [39]. In laboratory medicine, AI-driven automation and analytics have already demonstrated tangible benefits. Automated sample handling, intelligent quality control systems, and AI-assisted result interpretation have improved efficiency, reduced human error, and shortened turnaround times. More importantly, ML-based diagnostic models enhance analytical sensitivity and specificity by identifying subtle patterns that may escape conventional analysis [40]. Deep learning approaches in digital pathology and hematology, for example, have achieved diagnostic performance comparable to that of experienced specialists. Rather than replacing laboratory professionals, these systems augment human expertise by providing reliable decision support and consistency across high-workload environments. This synergy between human judgment and computational intelligence is likely to define the future role of AI in laboratory diagnostics [41]. Cancer biology represents another domain where AI and ML have demonstrated exceptional promise. Cancer is inherently heterogeneous, driven by complex interactions between genetic mutations, epigenetic modifications, environmental factors, and host immune responses. Machine learning models are uniquely suited to integrate genomic, transcriptomic, proteomic, imaging, and clinical data to characterize this complexity. AI-driven models that predict prognosis, therapeutic response, and disease progression are increasingly supporting precision oncology initiatives [42]. The ability to stratify patients and tailor therapies based on individual molecular profiles has profound implications for treatment effectiveness and patient survival. However, translating these models into clinical practice requires careful validation, as overfitting and data bias can limit generalizability across populations and healthcare settings. Beyond diagnostics and oncology, AI and ML are redefining molecular biomedical research more broadly. In molecular pathology, ML-based classification using DNA methylation profiling and digital histopathology has improved disease categorization and diagnostic accuracy [43]. In allergy research, AI algorithms that analyze protein sequences and structures have enhanced allergen identification and prediction, enabling more precise diagnosis and personalized treatment strategies. These applications illustrate how AI-driven molecular analysis can directly inform patient-specific care, bridging the gap between bench research and clinical practice. One of the most transformative impacts of AI in biomedical research is observed in drug discovery and pharmaceutical development. Conventional drug development pipelines are slow, expensive, and characterized by high attrition rates. AI-powered

platforms accelerate this process by screening vast chemical libraries, predicting drug target interactions, modeling toxicity, and optimizing lead compounds [44]. Breakthrough technologies such as AlphaFold have revolutionized protein structure prediction, providing detailed molecular insights that were previously unattainable through experimental methods alone. These advances enable rational drug design for complex diseases, including neurodegenerative and rare genetic disorders. While AI does not eliminate the need for experimental validation and clinical trials, it significantly improves efficiency and reduces the cost and risk associated with early-stage drug development [45]. Public health research also benefits substantially from AI and ML integration. Predictive models that analyze epidemiological, environmental, and socioeconomic data support early disease detection, outbreak prediction, and population-level risk stratification. During global health emergencies, AI-driven surveillance systems can enhance situational awareness and guide timely interventions. However, the reliability of these models depends heavily on data quality, representativeness, and transparency. In low and middle-income settings, data gaps and infrastructure limitations may reduce the effectiveness of AI-driven public health tools, underscoring the need for inclusive data strategies and global collaboration [46]. Despite these advances, significant challenges and limitations remain. Data quality is a persistent concern across all biomedical AI applications. AI models require large volumes of structured, labeled, and standardized data for training and validation. Variability in laboratory methods, inconsistent biomarker definitions, and fragmented data systems can undermine model performance. Bias in training datasets poses an even greater risk, as it can reinforce existing health disparities along lines of gender, ethnicity, or socioeconomic status. Addressing these issues requires deliberate efforts to curate diverse, representative datasets and adopt standardized data collection and reporting practices [47]. Ethical considerations further complicate AI integration in biomedical research. Issues related to data privacy, informed consent, algorithmic transparency, and accountability must be carefully managed. Many AI models function as black boxes, making it difficult to interpret how specific predictions are generated. This lack of explainability can reduce clinician trust and hinder regulatory approval. Developing interpretable models and establishing clear governance frameworks are, therefore, essential for responsible AI deployment in healthcare. Interdisciplinary collaboration emerges as a critical factor in overcoming these challenges. Effective AI integration requires coordinated efforts among laboratory scientists, clinicians, data scientists, bioinformaticians, engineers, ethicists, and policy makers. Such collaboration ensures that AI tools are biologically meaningful, clinically relevant, technically robust, and ethically sound. Interdisciplinary partnerships also support the standardization of data protocols, validation procedures, and performance benchmarks, which are essential for scaling AI solutions across institutions and regions. Education and workforce development play a central role in sustaining this transformation [48]. Many healthcare professionals lack formal training in AI and data science, which can hinder adoption and appropriate use. Continuous professional development programs and updated academic curricula that incorporate AI literacy are necessary to prepare both current and future professionals. A workforce that understands the strengths and limitations of AI is better positioned to integrate these tools into routine practice while maintaining critical oversight. Looking to the future, large-scale initiatives such as national and international data sharing programs reflect a growing recognition that AI-driven biomedical research depends on collaborative data ecosystems. Programs designed to generate high-quality, ethically sourced datasets will accelerate innovation while promoting equity and reproducibility. At the same time, regulatory frameworks must evolve to accommodate AI-based diagnostics and therapeutics, balancing innovation with patient safety [49]. AI and ML are reshaping biomedical research by enhancing diagnostic accuracy, accelerating drug discovery, enabling precision medicine, and strengthening public health responses. Their successful integration depends not only on technological advancement but also on data quality, ethical governance, interdisciplinary collaboration, and sustained education. When these elements align, AI-driven biomedical research has the potential to significantly improve patient outcomes and transform healthcare systems in an increasingly data-driven world.



## Conclusion

Artificial intelligence and machine learning have become integral to modern biomedical research, driving significant advances in diagnostics, molecular analysis, drug discovery, and public health. By enabling the analysis of complex, large-scale datasets, these technologies support more accurate diagnoses, personalized treatments, and efficient healthcare workflows. However, their successful integration depends on high-quality data, ethical governance, interdisciplinary collaboration, and continuous workforce training. Addressing challenges related to data bias, validation, and transparency is essential for clinical translation. With responsible implementation, AI and ML hold strong potential to transform biomedical research and improve patient outcomes.

## References

- [1] K. F. Bari, M. T. Salam, Tufael, S. E. Hasan, and A. R. Sunny, "Serum zinc and calcium level in patients with psoriasis," *J. Knowledge Learn. Sci. Technol.*, vol. 2, no. 3, pp. 7–14, 2023, doi: 10.60087/jklst.vol2.n3.p14.
- [2] Tufael, M. M. Rahman, et al., "Combined biomarkers for early diagnosis of hepatocellular carcinoma," *J. Angiother.*, vol. 8, no. 5, pp. 1–12, 2024, doi: 10.25163/angiotherapy.859665.
- [3] M. T. Salam, K. F. Bari, et al., "Emergence of antibiotic-resistant infections in ICU patients," *J. Angiother.*, vol. 8, no. 5, pp. 1–9, 2024, doi: 10.25163/angiotherapy.859560.
- [4] O. Faruk, S. E. Hasan, A. Jubayer, K. Akter, S. A. A. Shiam, K. Rahman, M. Y. Ali, and Tufael, "Microbial isolates from urinary tract infection and their antibiotic resistance pattern in Dhaka city of Bangladesh," *J. Knowledge Learn. Sci. Technol.*, vol. 2, no. 3, pp. 76–87, 2023, doi: 10.60087/jklst.vol2.n3.p87.
- [5] Tufael, A. Kar, M. H. O. Rashid, A. R. Sunny, A. Raposo, M. S. Islam, et al., "Diagnostic efficacy of tumor biomarkers AFP, CA19-9, and CEA in hepatocellular carcinoma patients," *J. Angiother.*, vol. 8, no. 4, Art. no. 9513, 2024, doi: 10.25163/angiotherapy.849513.
- [6] M. A. B. Siddique, A. Debnath, N. D. Nath, M. A. R. Biswash, and Tufael, "Advancing medical science through nanobiotechnology: prospects, applications, and future directions," *J. Primeasia*, vol. 1, no. 1, pp. 1–10, 2018, doi: 10.25163/primeasia.1110163.
- [7] Tufael and A. R. Sunny, "Artificial intelligence in addressing cost, efficiency, and access challenges in healthcare," *J. Primeasia*, vol. 4, no. 1, pp. 1–5, 2023, doi: 10.25163/primeasia.419798.
- [8] Tufael and M. S. Rana, "Impact and challenges of digital marketing in health care during the COVID-19 pandemic," *J. Primeasia*, vol. 4, no. 1, pp. 1–4, 2023, doi: 10.25163/primeasia.419756.
- [9] S. M. Hossain, M. R. Ashakin, et al., "IoT-based smart agriculture in Bangladesh: an overview," *Appl. Agric. Sci.*, vol. 1, no. 1, pp. 1–10, 2024, doi: 10.25163/agriculture.119563.
- [10] Tufael and D. M. M. M. Begum, "Hepatocellular carcinoma in a 55-year-old with chronic hepatitis B: a case report on diagnosis and management," *Asian Pac. J. Case Rep.*, vol. 1, no. 1, pp. 32–35, 2024, doi: 10.70818/apjcr.2024.v01i01.07.
- [11] M. T. Salam, K. F. Bari, et al., "Relationship of troponin I in septic patients without cardiac disease," *J. Primeasia*, vol. 5, no. 1, pp. 1–8, 2024, doi: 10.25163/primeasia.519733.
- [12] Tufael, S. E. Hasan, A. Jubayer, K. Akter, A. Akter, F. Akter, S. A. A. Shiam, and A. R. Sunny, "Effects of *Nigella sativa* and *Syzygium cumini* seed extracts on blood glucose levels in Swiss albino mice," *J. Knowledge Learn. Sci. Technol.*, vol. 2, no. 3, pp. 53–62, 2023, doi: 10.60087/jklst.vol2.n3.p62.
- [13] Tufael and A. R. Sunny, "Transforming healthcare with artificial intelligence: innovations, applications, and future challenges," *J. Primeasia*, vol. 3, no. 1, pp. 1–6, 2022, doi: 10.25163/primeasia.319802.
- [14] M. A. R. Biswash, M. A. B. Siddique, M. M. H. Shabuj, S. A. A. Aunni, M. M. Rahman, D.

- C. Das, and Tufael, “Advancing personalized cancer care: integrating CRISPR/Cas9 with next-generation sequencing technologies,” *J. Precision Biosci.*, vol. 6, no. 1, pp. 1–14, 2024, doi: 10.25163/biosciences.6110004.
- [15] Tufael and A. R. Sunny, “Artificial intelligence in healthcare: a review of diagnostic applications and impact on clinical practice,” *J. Primeasia*, vol. 2, no. 1, pp. 1–5, 2021, doi: 10.25163/primeasia.219816.
- [16] Tufael and A. R. Sunny, “Typhoid fever: recent advances in understanding, diagnosis, and management strategies for endemic regions,” *J. Primeasia*, vol. 1, no. 3, pp. 1–9, 2020, doi: 10.25163/primeasia.119803.
- [17] Tufael and A. R. Sunny, “Enhancing patient outcomes through innovative hospital management practices,” *J. Primeasia*, vol. 3, no. 1, pp. 1–8, 2022, doi: 10.25163/primeasia.319820.
- [18] N. D. Nath, A. Debnath, M. A. B. Siddique, and Tufael, “CRISPR-based approaches for diagnosing and treating infectious diseases,” *J. Primeasia*, vol. 5, no. 1, pp. 1–8, 2024, doi: 10.25163/primeasia.5110166.
- [19] Tufael, A. Kar, V. J. Upadhye, et al., “Serum biomarkers’ significance and gender-specific hepatocellular carcinoma insights of fisher patients in Bangladesh,” *J. Angiother.*, vol. 8, no. 1, pp. 1–9, 2024, doi: 10.25163/angiotherapy.819440.
- [20] G. Mahbub, M. O. Faruk, A. C. Das, T. A. Shaikat, M. T. Mia, R. Chowdhury, K. Rahman, S. A. Al Shiam, and Tufael, “Major causes of cerebral palsy among the children of Bangladesh,” *J. Knowledge Learn. Sci. Technol.*, vol. 2, no. 3, pp. 313–332, 2024, doi: 10.60087/jklst.vol2.n3.p332.
- [21] A. K. Manica, M. R. Islam, M. A. B. Siddique, M. F. Akter, and Tufael, “Tanshinone IIA as a promising natural inhibitor of the STING pathway: a computational exploration toward neuroinflammatory therapy,” *Aust. Herbal Insight*, vol. 7, no. 1, pp. 1–13, 2024, doi: 10.25163/ahi.719931.
- [22] A. K. Manica, M. A. B. Siddique, Tufael, M. F. Akter, and M. R. Islam, “Targeted drug repurposing in precision oncology reveals celecoxib as a GSK-3 $\beta$  inhibitor in hepatocellular carcinoma,” *J. Precision Biosci.*, vol. 6, no. 1, pp. 1–13, 2024, doi: 10.25163/biosciences.6110440.
- [23] Tufael and M. S. Ullah, “Role of human microbiome in non-communicable diseases: a public health perspective,” *Clin. Epidemiol. Public Health*, vol. 2, no. 1, pp. 1–8, 2024, doi: 10.25163/health.2110279.
- [24] N. D. Nath, A. Debnath, M. A. B. Siddique, and Tufael, “Combating antimicrobial resistance: public health policies, community awareness and global surveillance,” *Clin. Epidemiol. Public Health*, vol. 2, no. 1, pp. 1–8, 2024, doi: 10.25163/health.2110280.
- [25] K. Begum and S. E. Hasan, “Optimizing healthcare performance with business analytics,” *Pathfinder of Research*, vol. 1, no. 3, pp. 34–48, Dec. 2023, doi: 10.69937/pf.por.1.3.58.
- [26] A. K. Manica, Tufael, M. A. B. Siddique, M. F. Akter, and M. R. Islam, “In silico repurposing of FDA-approved drugs targeting Keap1–NRF2 axis in hepatocellular carcinoma for precision therapy,” *J. Precision Biosci.*, vol. 5, no. 1, pp. 1–14, 2023.
- [27] Tufael, A. Debnath, M. A. B. Siddique, and N. D. Nath, “Microbial therapeutics in cancer treatment: challenges and opportunities in breast cancer management,” *Clin. Epidemiol. Public Health*, vol. 1, no. 1, pp. 1–7, 2023.
- [28] M. R. Alam, R. Chowdhury, S. A. Sazzad, et al., “The role of business finance in sustainable development: insights from spinning mills,” *Appl. Agric. Sci.*, vol. 1, no. 1, pp. 1–9, 2023, doi: 10.25163/agriculture.119581.
- [29] M. R. Islam, A. K. Manica, M. F. Akter, M. A. B. Siddique, and Tufael, “In silico drug-likeness and safety profiling of tinosporaside: a natural alternative to celecoxib for COX-2 inhibition,” *J. Primeasia*, vol. 4, no. 1, pp. 1–11, 2023.

- [30] M. M. H. Shabuj, B. Ahmed, M. M. Rahman, S. A. A. Aunni, A. A. Numan, M. S. Akter, and Tufael, "Advancing personalized treatment for hepatocellular carcinoma: integrating targeted therapies, precision medicine, and bioengineering for improved outcomes," *J. Primeasia*, vol. 1, no. 2, pp. 1–13, 2019, doi: 10.25163/primeasia.1110015.
- [31] M. F. Akter, M. R. Islam, A. K. Manica, M. A. B. Siddique, and Tufael, "Structural and pharmacological insights into Withaferin A binding to mutant p53 (R248Q): multi-faceted inhibitor in cancer treatment," *J. Angiother.*, vol. 6, no. 2, pp. 1–11, 2022.
- [32] P. K. M. M. U. and Tufael, "Artificial intelligence and applied machine learning to improve pre-analytical and post-analytical processes in laboratory medicine," *J. AI Mach. Learn. Deep Learn.*, vol. 1, no. 1, pp. 1–10, 2025, doi: 10.25163/ai.1110407.
- [33] M. R. Islam, M. F. Akter, M. A. B. Siddique, Tufael, and A. K. Manica, "Integrating clinical data and molecular profiling to predict antibiotic-induced anaphylaxis: a comparative study of ceftriaxone and meropenem," *J. Primeasia*, vol. 6, no. 1, pp. 1–11, 2025, doi: 10.25163/primeasia.6110446.
- [34] N. Chowdhury, N. C. Mahat, Tufael, and M. A. B. Siddique, "TGF- $\beta$ 1 as a molecular target and vitamin D interaction in diabetic nephropathy: a bio-clinical correlation study," *Integr. Biomed. Res.*, vol. 9, no. 1, pp. 1–8, 2025, doi: 10.25163/biomedical.9110450.
- [35] Tufael and P. K. M. M. U., "Machine learning in cancer biology: transforming diagnosis, prognosis, and treatment in modern medical research," *J. AI Mach. Learn. Deep Learn.*, vol. 1, no. 1, pp. 1–10, 2025, doi: 10.25163/ai.1110405.
- [36] M. F. Akter, A. K. Manica, M. A. B. Siddique, Tufael, M. R. Islam, and S. Nusrat, "Structural insights into TEM-1  $\beta$ -lactamase-mediated ceftriaxone resistance in *Escherichia coli*: a molecular docking and toxicity analysis," *Microb. Bioact.*, vol. 8, no. 1, pp. 1–11, 2025, doi: 10.25163/microbbioacts.8110447.
- [37] M. S. Amin, M. J. Rashid, Tufael, and A. Rahman, "Probiotics as emerging neurotherapeutics in spinal cord injury: modulating inflammation, infection, and regeneration," *Microb. Bioact.*, vol. 8, no. 1, pp. 1–11, 2025, doi: 10.25163/microbbioacts.8110290.
- [38] V. J. Upadhye and M. S. Saif, *Chemiluminescence: Based Correlation of Biomarkers in Liver Cancer*. Research Beacon Publication, Jun. 30, 2025.
- [39] Tufael and M. A. B. Siddique, "Bioinformatics in microbiology: reviewing the role of bioinformatics in studying microbial genomics, metagenomics, and phylogenetics," *Microb. Bioact.*, vol. 8, no. 1, pp. 1–11, 2025, doi: 10.25163/microbbioacts.8110370.
- [40] Tufael, M. J. Rashid, M. S. Amin, and A. Rahman, "Unmasking the dual threat of mRNA vaccines: spike protein toxicity, nanorobotic vectoring, and the promise of signal-based medicine," *J. Precision Biosci.*, vol. 7, no. 1, pp. 1–10, 2025, doi: 10.25163/biosciences.7110288.
- [41] Tufael, M. F. Akter, M. R. Islam, M. A. B. Siddique, N. Hassan, A. A. Numan, A. A. Naher, M. M. H. Shabuj, A. K. Manica, B. Shaikat, and T. B. Rabbani, "Encoded resistance: structural disruption and signaling crosstalk undermine sorafenib binding in mutant VEGFR2-driven HCC," *Paradise*, vol. 1, no. 1, pp. 1–8, 2025, doi: 10.25163/paradise.1110427.
- [42] S. F. Tamanna, M. Noyel, M. Fatin, M. H. Rabbi, D. C. Das, and Tufael, "Nanotechnology in agriculture and water quality management," *Appl. Agric. Sci.*, vol. 3, no. 1, pp. 1–12, 2025, doi: 10.25163/agriculture.3110170.
- [43] K. F. Bari, M. T. Salam, M. Maliha, B. C. Singha, A. F. Islam, N. K. Oni, S. Hossain, M. S. Ullah, M. Islam, and Tufael, "Observational study on the clinical manifestations and features of dengue fever," *J. Primeasia*, vol. 6, no. 1, pp. 1–9, 2025, doi: 10.25163/primeasia.6110203.
- [44] A. Debnath, M. A. B. Siddique, N. D. Nath, M. A. R. Biswash, and Tufael, "Emerging alternatives to PCR for efficient nucleic acid amplification," *J. Primeasia*, vol. 6, no. 1, pp.

1–11, 2025, doi: 10.25163/primeasia.6110167.

- [45] M. J. Rashid, M. S. Amin, Tufael, and A. Rahman, “Unintended genetic consequences of mRNA vaccines: evaluating risks of transcriptional disruption, HLA alteration, and genomic integration,” *J. Precision Biosci.*, vol. 7, no. 1, pp. 1–11, 2025, doi: 10.25163/biosciences.7110287.
- [46] M. S. S. Khan and Tufael, “Innovations in cancer research and treatment,” *J. Precision Biosci.*, vol. 7, no. 1, pp. 1–11, 2025, doi: 10.25163/ahi.7120050.
- [47] C. Sarkar, A. Hasnat, M. M. Rahman, M. Maliha, B. C. Singha, and Tufael, “Bacterial surface components and toxins in cancer development: mechanisms of oncogenesis and therapeutic implications,” *Microb. Bioact.*, vol. 8, no. 1, pp. 1–12, 2025, doi: 10.25163/microbbioacts.8110174
- [48] A. K. Goel and L. Polepeddi, "Jill Watson: A virtual teaching assistant for online education," in *Learning Engineering for Online Education*, London, UK: Routledge, 2018. <https://doi.org/10.4324/9781351186193-7>
- [49] L. G. McCoy et al., "What do medical students actually need to know about artificial intelligence?" *NPJ Digital Medicine*, vol. 3, Art. no. 86, 2020. <https://doi.org/10.1038/s41746-020-0294-7>
- [50] W. N. Price and I. G. Cohen, "Privacy in the age of medical big data," *Nature Medicine*, vol. 25, pp. 37-43, 2019. <https://doi.org/10.1038/s41591-018-0272-7>
- [51] F. W. Stahnisch and M. Verhoef, "The Flexner Report of 1910 and its impact on complementary and alternative medicine and psychiatry in North America in the 20th century," *Evidence-Based Complementary and Alternative Medicine*, vol. 2012, Art. no. 647896, 2012. <https://doi.org/10.1155/2012/647896>