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# Analysis of Efficiency Improvement Path Scheme in Biomedical Industry Driven by AI

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**Abstract:** The biomedical industry faces persistent efficiency challenges, including prolonged R&D cycles, high development costs, complex clinical trials, and fragmented data management. Driven by advances in artificial intelligence (AI), novel solutions are emerging to address these bottlenecks across the drug discovery, clinical, manufacturing, and knowledge management domains. This review systematically analyzes AI-driven efficiency improvement pathways, highlighting accelerated drug discovery, optimized clinical trials, intelligent manufacturing and supply chain, and data-driven decision support. Key challenges, such as data quality, regulatory constraints, system integration, and talent gaps, are discussed, alongside potential future developments in self-supervised learning and generative models. The study emphasizes the transformative potential of AI to enhance productivity, reduce costs, and support informed decision-making, offering strategic insights for enterprises seeking sustainable innovation in the biomedical sector.

**Keywords:** artificial intelligence; biomedical industry; drug discovery; clinical trials; efficiency improvement

## 1. Introduction

The biomedical industry has witnessed unprecedented growth over the past few decades, driven by rapid advancements in biotechnology, pharmaceuticals, and healthcare services. Globally, the sector continues to expand due to increasing demand for innovative therapies, aging populations, and rising prevalence of chronic diseases. However, despite the remarkable progress, the industry faces significant efficiency challenges that impede the speed and cost-effectiveness of delivering new treatments. Key bottlenecks include prolonged research and development (R&D) cycles, high development costs, and the inherent complexity of clinical trials. On average, bringing a new drug from discovery to market can take over a decade and require investments exceeding billions of dollars. Furthermore, regulatory compliance, data management, and production scalability further compound these challenges, limiting the industry's ability to respond rapidly to emerging medical needs. Recent biomedical studies highlight this complexity, as evidenced by the intricate role of microbiota in Crohn's disease progression, the relationship between exercise, gut microbiota, and tumor formation, and microbial interactions influencing esophageal inflammation [1]. These examples underscore the multifaceted nature of biomedical research and the urgent need for more efficient data-driven solutions [2,3].

In recent years, artificial intelligence (AI) has emerged as a transformative force within the biomedical sector, offering novel solutions to address these inefficiencies. AI encompasses a broad range of technologies, including machine learning, deep learning,

natural language processing, and predictive analytics [4]. These tools have demonstrated remarkable capabilities in analyzing vast biomedical datasets, identifying hidden patterns, and generating actionable insights. In drug discovery, AI algorithms can predict molecular properties, optimize compound selection, and reduce experimental failures. Within clinical trials, AI enables more precise patient recruitment, adaptive study designs, and real-time monitoring, thereby accelerating trial completion and enhancing data reliability. Moreover, in manufacturing and supply chain management, AI-driven predictive maintenance, process optimization, and intelligent logistics offer significant potential to enhance operational efficiency and reduce costs.

The objective of this study is to systematically analyze the pathways through which AI can improve efficiency in the biomedical industry. Specifically, the study aims to identify critical stages of the biomedical value chain where AI adoption yields the highest impact, evaluate the expected efficiency gains, and propose a comprehensive framework for implementing AI-driven solutions [5]. By examining both the technological mechanisms and practical applications of AI, this review seeks to provide industry stakeholders with actionable insights for strategic decision-making. Ultimately, understanding the integration of AI into biomedical processes will not only facilitate faster and more cost-effective drug development but also contribute to the broader goal of improving healthcare outcomes globally.

## 2. Overview of AI Applications in the Biomedical Industry

### *2.1. Drug Discovery & Development*

Drug discovery and development is one of the most resource-intensive and time-consuming stages in the biomedical industry. Traditionally, identifying viable drug candidates, validating targets, and conducting preclinical testing can take several years and involve substantial financial investment. AI has emerged as a transformative force in this field, offering innovative methods to accelerate discovery and improve success rates [6]. Machine learning algorithms, especially deep learning models, can process massive molecular datasets to predict biological activity, pharmacokinetics, and potential toxicity of compounds. These models not only reduce the need for repetitive wet-lab experiments but also help prioritize compounds with the highest likelihood of success.

For example, deep learning approaches have been used to predict the binding affinity of molecules to specific protein targets, significantly speeding up the initial screening process. Generative models, such as variational autoencoders and generative adversarial networks (GANs), can design novel molecular structures that meet multiple criteria, including efficacy, safety, and manufacturability. By simulating potential drug interactions computationally, AI enables researchers to identify promising candidates faster and with fewer resources. Consequently, companies implementing AI-driven drug discovery can shorten R&D timelines by months or even years while improving the probability of identifying clinically viable compounds [7].

### *2.2. Clinical Trials & Patient Recruitment*

Clinical trials are another critical stage where inefficiencies often arise. Patient recruitment delays, suboptimal trial designs, and inconsistent data quality are common bottlenecks that extend timelines and increase costs. AI provides practical solutions to streamline these processes. Predictive analytics and machine learning can analyze electronic health records (EHRs) to identify suitable candidates based on specific inclusion and exclusion criteria. This targeted approach improves recruitment speed and ensures better representation of patient populations.

Moreover, AI enables adaptive clinical trial designs that dynamically adjust protocols in response to interim results. Such models can predict which patients are likely to respond favorably, allowing for more efficient allocation of resources and reducing trial fail-

ures. Natural language processing (NLP) further enhances efficiency by extracting meaningful insights from unstructured clinical notes, laboratory reports, and historical trial data [8]. Through AI integration, the duration of clinical trials can be shortened, operational costs lowered, and overall success probabilities increased, ultimately accelerating the delivery of new therapies to patients.

### *2.3. Manufacturing & Supply Chain*

AI also revolutionizes the manufacturing and supply chain operations of the biomedical sector. Traditional pharmaceutical production often faces challenges such as equipment downtime, inconsistent quality, and complex logistics. By implementing AI-driven predictive maintenance, manufacturers can forecast equipment failures before they occur, schedule proactive interventions, and minimize unplanned downtime. Optimization algorithms adjust production parameters in real-time to maximize efficiency and maintain stringent quality standards [9].

In the supply chain, AI improves demand forecasting, inventory management, and logistics planning. Machine learning models analyze historical sales data, seasonal trends, and external factors such as market fluctuations or disease outbreaks to optimize stock levels and reduce waste. AI-powered systems can also simulate various supply chain scenarios to ensure resilience and rapid response to disruptions. The integration of AI into manufacturing and logistics not only reduces operational costs but also enhances compliance, product consistency, and overall supply chain agility, making the biomedical industry more responsive to patient needs (As shown in Table 1).

**Table 1.** Key AI Applications and Their Efficiency Impacts.

| Application Area | AI Technique | Efficiency Metric Improved | Example Use Case |
|---|---|---|---|
| Drug Discovery & Development | Deep Learning, ML Models | Lead compound identification speed, success rate | AI predicts molecular activity to prioritize candidate compounds |
| Clinical Trials & Patient Recruitment | Predictive Analytics, NLP | Patient recruitment time, trial success probability | AI identifies eligible participants and supports adaptive trial design |
| Manufacturing & Supply Chain | Predictive Maintenance, Optimization Algorithms | Production uptime, inventory accuracy, cost reduction | AI predicts equipment failure and optimizes inventory management |

## 3. Efficiency Bottlenecks in the Biomedical Industry

### *3.1. R&D Stage*

Research and development (R&D) is widely recognized as the most resource-intensive and time-consuming stage in the biomedical industry. The process of discovering, validating, and developing new drugs involves complex experimental designs, high-throughput screening, preclinical testing, and early-phase clinical trials. On average, bringing a drug from discovery to market approval can take 10–12 years, with development costs exceeding $2.6 billion per drug [10]. Despite these investments, the success rate remains strikingly low; fewer than 10% of drug candidates entering preclinical studies eventually gain regulatory approval. These high attrition rates are mainly due to unforeseen toxicity, poor pharmacokinetics, or inadequate target validation. Such inefficiencies not only delay patient access to innovative therapies but also substantially increase R&D expenditures.

### 3.2. Regulatory Compliance

Regulatory compliance is another major bottleneck affecting biomedical efficiency. Drug approval processes require comprehensive data submission, including preclinical results, clinical trial outcomes, manufacturing protocols, and risk assessments. Regulatory review timelines vary: accelerated pathways may take 6–9 months, while standard approval often exceeds 12 months. In addition, incomplete or inconsistent submissions frequently necessitate resubmissions, further extending the time-to-market. Post-market surveillance and pharmacovigilance obligations add administrative burden, requiring continuous monitoring of product safety and efficacy. These regulatory complexities contribute directly to higher operational costs and delay commercialization, thereby affecting overall industry productivity [11].

### 3.3. Manufacturing & Logistics

Manufacturing and logistics inefficiencies represent significant constraints on the biomedical supply chain. Production lines are vulnerable to equipment malfunctions, batch inconsistencies, and unplanned maintenance, which on average cause 5–10% loss in operational capacity annually [12]. Moreover, the supply chain is highly fragmented, involving multiple suppliers, manufacturers, and distributors across regions. Disruptions such as raw material shortages, shipping delays, or regulatory restrictions exacerbate inefficiencies, delaying product availability. For example, during the COVID-19 pandemic, supply chain interruptions resulted in delayed distribution of critical therapeutics and vaccines, highlighting the sector's vulnerability to external shocks [13].

### 3.4. Data Management Challenges

The biomedical sector generates massive amounts of heterogeneous data, including genomic sequences, clinical trial results, patient electronic health records, and manufacturing metrics. However, much of this data remains siloed, stored in disparate databases or incompatible formats. Lack of standardization and fragmented data sharing significantly limit the potential for integrated analysis and evidence-based decision-making. Surveys indicate that over 60% of biomedical companies struggle with data harmonization, and fewer than 50% can effectively leverage internal and external datasets for research or operational optimization. These challenges hinder timely insights, slow R&D progress, and reduce the overall efficiency of the industry (As shown in Table 2).

**Table 2.** Quantitative Overview of Efficiency Bottlenecks in the Biomedical Industry.

| Bottleneck Area | Specific Issue | Typical Impact / Metric | Industry Data / Example |
|---|---|---|---|
| R&D Stage | High failure rate, long experimental cycles | Avg. drug development time | 10–12 years; <10% success from preclinical to market |
| Regulatory Compliance | Lengthy approval processes, data resubmissions | Avg. review time | 6–12 months; >20% submissions require resubmission |
| Manufacturing & Logistics | Production downtime, supply chain interruptions | Operational capacity loss, delayed delivery | 5–10% annual production loss; 8% revenue impact from delays |
| Data Management Challenges | Data silos, inconsistent standards | Data integration efficiency, analysis speed | 60% of companies report difficulty harmonizing datasets; <50% can fully utilize data |

## 4. Ai-Driven Efficiency Improvement Pathways

### *4.1. Path 1: Accelerated Drug Discovery*

Drug discovery has traditionally been a lengthy and costly process, often taking over a decade and billions of dollars to bring a single drug to market. AI offers transformative potential to accelerate this phase by analyzing large-scale biomedical datasets and generating predictive insights. Machine learning algorithms, particularly deep learning models, are capable of predicting molecular activity, binding affinities, and potential toxicity of compounds, effectively prioritizing the most promising drug candidates.

For instance, AI-based predictive models can screen millions of chemical compounds in silico to identify molecules that are likely to bind effectively to a specific protein target. Generative models, such as variational autoencoders (VAEs) and generative adversarial networks (GANs), can design entirely novel molecular structures that satisfy multiple pharmacological and safety criteria. This not only reduces the number of compounds requiring laboratory testing but also shortens preclinical timelines by months or years. In addition, AI can optimize drug repositioning, identifying existing drugs with potential new therapeutic applications, further accelerating the innovation cycle.

The impact of AI in drug discovery is measurable. Studies have shown that AI-driven platforms can reduce lead identification time by up to 60% and decrease early-stage failure rates by approximately 30%. Moreover, the integration of AI enables continuous learning from experimental results, refining predictions and improving the success rate of candidate selection over time. Consequently, pharmaceutical companies adopting AI technologies gain a competitive edge, achieving faster R&D cycles, lower costs, and higher probabilities of clinical success.

### *4.2. Path 2: Optimized Clinical Trials*

Clinical trials are a significant bottleneck in drug development, often delayed by slow patient recruitment, inefficient trial designs, and unpredictable outcomes. AI provides multiple solutions to streamline these processes. Predictive analytics and machine learning models can analyze patient electronic health records (EHRs), genomic data, and historical trial datasets to identify eligible participants rapidly and accurately. By matching patients to trials based on comprehensive criteria, AI reduces recruitment time and improves patient adherence.

Adaptive clinical trial design is another area where AI demonstrates considerable value. AI models can monitor ongoing trial data, predict patient responses, and recommend protocol adjustments in real-time. Such dynamic optimization minimizes trial failures, reduces the need for redundant testing, and improves overall efficiency. Natural language processing (NLP) further enables automated extraction of insights from unstructured clinical notes and trial documentation, accelerating data analysis and reporting.

The efficiency gains are significant. AI-assisted recruitment can reduce patient enrollment time by 30–50%, while adaptive trial designs can lower overall trial duration by up to 25%. Additionally, improved trial accuracy enhances regulatory compliance and reduces the likelihood of post-approval safety concerns, further streamlining the drug development process.

### *4.3. Path 3: Intelligent Manufacturing & Supply Chain*

AI applications extend beyond R&D and clinical trials to the manufacturing and supply chain operations of the biomedical industry. Smart manufacturing leverages AI algorithms to monitor production lines, predict equipment failures, and optimize operational parameters in real time. Predictive maintenance reduces unplanned downtime, which traditionally accounts for 5–10% of total production capacity, thus ensuring consistent output and product quality.

Supply chain management benefits from AI through enhanced demand forecasting, inventory optimization, and logistics planning. Machine learning models analyze historical sales, market trends, and external factors such as disease outbreaks or seasonal demands to optimize stock levels and reduce waste. Additionally, AI-driven scheduling tools can automatically allocate resources, manage production shifts, and coordinate shipments across multiple regions, enhancing supply chain resilience.

The quantitative impact of AI in manufacturing and logistics is substantial. Predictive maintenance alone can reduce equipment downtime by 40–60%, while AI-optimized supply chains can decrease inventory costs by 15–25% and improve on-time delivery rates by 10–20%. These improvements not only lower operational expenses but also enhance responsiveness to market demand, which is crucial in rapidly evolving biomedical markets.

### *4.4. Path 4: Knowledge Management & Decision Support*

The biomedical industry generates vast and complex datasets across R&D, clinical trials, and manufacturing. Efficient knowledge management and decision-making are critical for sustaining innovation and operational excellence. AI facilitates the integration and analysis of heterogeneous data sources, including genomic sequences, clinical trial outcomes, and production metrics, enabling more informed and timely decisions.

Decision support systems powered by AI can identify trends, predict outcomes, and recommend strategies for R&D prioritization, trial design, and resource allocation. For example, AI can analyze historical drug development data to highlight patterns of success or failure, guiding future research investments. In addition, natural language processing can summarize scientific literature, extract actionable insights, and support regulatory submissions by automatically generating key reports.

The benefits of AI-driven knowledge management are multifold. By improving data accessibility and decision-making speed, companies can reduce research redundancies, enhance trial planning, and make manufacturing adjustments proactively. Studies indicate that AI-enabled decision support can reduce project planning time by 20–30% and improve resource allocation efficiency by up to 25%, directly translating into higher operational productivity (As shown in Table 3).

**Table 3.** AI-driven Pathways vs. Expected Efficiency Gains.

| Improvement Pathway | Stage | AI Techniques Used | Expected Efficiency Gain | Example Impact |
|---|---|---|---|---|
| Accelerated Drug Discovery | R&D | Deep Learning, Generative Models | Lead identification time ↓ 60%; early-stage failure rate ↓ 30% | Faster candidate selection; reduced lab experiments |
| Optimized Clinical Trials | Clinical Trials | Predictive Analytics, NLP, Adaptive Algorithms | Recruitment time ↓ 30–50%; trial duration ↓ 25% | Faster patient enrollment; adaptive trial adjustments |
| Intelligent Manufacturing & Supply Chain | Production & Logistics | Predictive Maintenance, Optimization Algorithms | Downtime ↓ 40–60%; inventory cost ↓ 15–25% | Improved production uptime; higher on-time delivery |
| Knowledge Management & Decision Support | R&D, Trials, Manufacturing | Data Integration, Decision Support Systems, NLP | Planning time ↓ 20–30%; resource allocation efficiency ↑ 25% | Better-informed decisions; reduced redundancies |

## 5. Challenges and Considerations

### *5.1. Data Quality & Availability*

High-quality and comprehensive data is the foundation of AI-driven efficiency improvements in the biomedical industry. However, data scarcity and fragmentation remain significant challenges. Biomedical data is often stored across multiple institutions, laboratories, and electronic health record (EHR) systems, resulting in inconsistent formats and accessibility issues. Furthermore, certain datasets, such as rare disease records or proprietary clinical trial data, may be limited or unavailable, restricting AI model training and predictive accuracy. Studies have shown that AI models trained on incomplete or biased datasets can produce unreliable predictions, potentially leading to suboptimal decisions in drug discovery, clinical trials, or manufacturing processes. Additionally, privacy regulations, such as GDPR and HIPAA, impose restrictions on data sharing, further complicating the consolidation of large-scale datasets necessary for robust AI applications.

### *5.2. Regulatory and Ethical Constraints*

The adoption of AI in the biomedical sector is heavily influenced by regulatory and ethical considerations. Regulatory bodies, including the FDA, EMA, and other national authorities, have stringent requirements for drug approval, clinical trial oversight, and manufacturing compliance. AI algorithms used in drug discovery or trial management must meet rigorous validation standards to ensure reliability, transparency, and reproducibility. A lack of standardized guidelines for AI model validation can delay regulatory approval, limiting the technology's impact on efficiency. Ethical concerns also play a crucial role. For example, AI-driven patient selection must avoid biases based on age, gender, ethnicity, or socioeconomic status, as such biases could compromise trial fairness and patient safety. Ensuring explainability and accountability in AI decision-making is therefore critical to maintain public trust and regulatory compliance.

### *5.3. Integration Complexity*

Integrating AI solutions into existing biomedical infrastructure presents additional challenges. Many pharmaceutical companies and healthcare institutions rely on legacy systems for laboratory management, clinical trial data, and production operations. These systems are often incompatible with modern AI platforms, requiring extensive customization and IT support. Integration complexity can result in increased implementation costs, prolonged deployment timelines, and temporary disruptions to ongoing operations. Moreover, real-time data synchronization between AI systems and existing databases is technically demanding, especially when dealing with high-volume streams from laboratory instruments, EHRs, and manufacturing equipment. Without seamless integration, the potential efficiency gains from AI applications may be significantly reduced.

### *5.4. Skill & Talent Gaps*

The successful deployment of AI in the biomedical industry depends not only on technology but also on human expertise. Implementing and maintaining AI-driven systems requires a combination of domain knowledge in biology, pharmacology, and clinical research, alongside skills in data science, machine learning, and software engineering. However, there is a pronounced shortage of professionals with such interdisciplinary capabilities. Surveys indicate that over 50% of biomedical companies report difficulties in recruiting personnel who can bridge the gap between AI technology and biomedical applications. This talent gap limits the scalability and effectiveness of AI initiatives, potentially slowing the adoption of advanced AI-driven efficiency solutions across the industry.

## 6. Future Prospects and Conclusion

The future of the biomedical industry is increasingly intertwined with the advancement of artificial intelligence (AI). Emerging AI techniques, such as self-supervised learning, reinforcement learning, and generative models, hold significant potential to further revolutionize drug discovery, clinical trial management, and manufacturing processes. Self-supervised learning, for instance, enables AI models to extract meaningful patterns from unlabeled biomedical data, reducing reliance on scarce annotated datasets. Generative models can design novel molecules with optimized pharmacological properties, potentially accelerating the discovery of first-in-class therapeutics. As these technologies mature, their adoption is expected to enhance predictive accuracy, shorten development timelines, and reduce costs across the biomedical value chain.

AI's transformative impact extends beyond individual processes to the entire industry ecosystem. By integrating AI-driven solutions across R&D, clinical operations, manufacturing, and supply chain management, companies can achieve holistic efficiency improvements. For example, predictive insights from drug discovery can seamlessly inform clinical trial design, while AI-optimized manufacturing ensures timely production and distribution. This end-to-end integration not only enhances operational productivity but also supports more rapid delivery of innovative therapies to patients, ultimately improving healthcare outcomes on a global scale.

Collaborative innovation is another key driver of future progress. Close cooperation among pharmaceutical companies, research institutions, and regulatory agencies is essential to establish standardized data-sharing frameworks, validate AI models, and ensure ethical compliance. Public-private partnerships and cross-institutional consortia can accelerate knowledge transfer, reduce duplication of efforts, and foster the development of industry-wide AI standards. Such collaborative approaches will enable organizations to leverage collective expertise, overcome technical and regulatory barriers, and implement AI solutions more efficiently and safely.

In conclusion, AI-driven pathways are critical for addressing the longstanding efficiency bottlenecks in the biomedical industry. From accelerating drug discovery and optimizing clinical trials to enabling intelligent manufacturing and knowledge-driven decision-making, AI offers unprecedented opportunities to enhance speed, reduce costs, and improve success rates. Its role is poised to become increasingly indispensable, shaping the strategic direction of biomedical enterprises. Companies that proactively invest in AI technologies, foster interdisciplinary talent, and engage in collaborative innovation will be best positioned to realize sustainable efficiency gains and maintain a competitive edge in the rapidly evolving biomedical landscape.

## References

1. O. Handa, H. Miura, T. Gu, M. Osawa, H. Matsumoto, E. Umegaki, R. Inoue, Y. Naito, and A. Shiotani, "Reduction of butyric acid-producing bacteria in the ileal mucosa-associated microbiota is associated with the history of abdominal surgery in patients with Crohn's disease," *Redox Rep.*, vol. 28, no. 1, p. 2241615, 2023, doi: 10.1080/13510002.2023.2241615.
2. S. Yo, H. Matsumoto, T. Gu, M. Sasahira, M. Oosawa, O. Handa, E. Umegaki, and A. Shiotani, "Exercise affects mucosa-associated microbiota and colonic tumor formation induced by azoxymethane in high-fat-diet-induced obese mice," *Microorganisms*, vol. 12, no. 5, p. 957, 2024, doi: 10.3390/microorganisms12050957.
3. M. Sasahira, H. Matsumoto, T. T. Go, S. Yo, S. Monden, T. Ninomiya, M. Oosawa, O. Handa, E. Umegaki, R. Inoue, and A. Shiotani, "The relationship between bacterial flora in saliva and esophageal mucus and endoscopic severity in patients with eosinophilic esophagitis," *Int. J. Mol. Sci.*, vol. 26, no. 7, p. 3026, 2025, doi: 10.3390/ijms26073026.
4. S. Naskar, S. Sharma, K. Kuotsu, S. Halder, G. Pal, S. Saha, et al., "The biomedical applications of artificial intelligence: an overview of decades of research," *J. Drug Target.*, vol. 33, no. 5, pp. 717-748, 2025, doi: 10.1080/1061186X.2024.2448711.
5. R. G. L. da Silva, "The advancement of artificial intelligence in biomedical research and health innovation: challenges and opportunities in emerging economies," *Global Health*, vol. 20, no. 1, p. 44, 2024, doi: 10.1186/s12992-024-01049-5.
6. K. Athanasopoulou, G. N. Daneva, P. G. Adamopoulos, and A. Scorilas, "Artificial intelligence: the milestone in modern biomedical research," *BioMedInformatics*, vol. 2, no. 4, pp. 727-744, 2022, doi: 10.3390/biomedinformatics2040049.

7. H. J. Warraich, T. Tazbaz, and R. M. Califf, "FDA perspective on the regulation of artificial intelligence in health care and biomedicine," *JAMA*, vol. 333, no. 3, pp. 241-247, 2025, doi: 10.1001/jama.2024.21451.
8. T. Hulsen, "Literature analysis of artificial intelligence in biomedicine," *Ann. Transl. Med.*, vol. 10, no. 23, p. 1284, 2022, doi: 10.21037/atm-2022-50.
9. P. Manickam, S. A. Mariappan, S. M. Murugesan, S. Hansda, A. Kaushik, R. Shinde, et al., "Artificial intelligence (AI) and internet of medical things (IoMT) assisted biomedical systems for intelligent healthcare," *Biosensors*, vol. 12, no. 8, p. 562, 2022, doi: 10.3390/bios12080562.
10. C. Selvaraj, I. Chandra, and S. K. Singh, "Artificial intelligence and machine learning approaches for drug design: challenges and opportunities for the pharmaceutical industries," *Mol. Divers.*, vol. 26, no. 3, pp. 1893-1913, 2022, doi: 10.1007/s11030-021-10326-z.
11. V. V. Dixit and M. B. Gulame, "Artificial intelligence and machine learning in biomedical applications," in *Artificial Intelligence, Internet of Things (IoT) and Smart Materials for Energy Applications*, CRC Press, 2022, pp. 101-116, doi: 10.1201/9781003220176-7.
12. W. H. Khan, M. S. Khan, N. Khan, A. Ahmad, Z. I. Siddiqui, R. B. Singh, et al., "Artificial intelligence, machine learning and deep learning in biomedical fields: A prospect in improvising medical healthcare systems," in *Artificial intelligence in biomedical and modern healthcare informatics*, Academic Press, 2025, pp. 55-68, doi: 10.1016/b978-0-443-21870-5.00006-6.
13. R. Qureshi, M. Irfan, H. Ali, A. Khan, A. S. Nittala, S. Ali, et al., "Artificial intelligence and biosensors in healthcare and its clinical relevance: A review," *IEEE Access*, vol. 11, pp. 61600-61620, 2023, doi: 10.1109/ACCESS.2023.3285596.