

# Impact of Artificial Intelligence on Modern Healthcare Technology: Applications, Challenges and Future Perspectives

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## Abstract

Artificial intelligence (AI) has moved from being primarily a subject of computational research to becoming an increasingly visible part of modern healthcare. The change has been driven by the rapid growth of digital health records, medical imaging, genomic information, wearable devices and other sources of health-related data. These developments have created opportunities for computational methods to assist with tasks that are difficult to perform efficiently through conventional approaches alone. Machine learning, deep learning, natural language processing, computer vision and, more recently, generative AI are now being investigated across a broad range of healthcare applications. The influence of AI is particularly evident in medical imaging, disease prediction, clinical decision support, drug discovery, pharmacovigilance, personalized medicine and remote patient monitoring. In pharmaceutical research, machine-learning approaches can be used to explore chemical and biological datasets, predict molecular properties and support the identification and optimization of potential drug candidates. However, the transition from a promising computational result to a clinically useful product is not straightforward. AI systems may perform differently when applied to populations, healthcare environments or datasets that differ from those used during development. Problems related to data quality, bias, interpretability, privacy and cybersecurity therefore remain important.

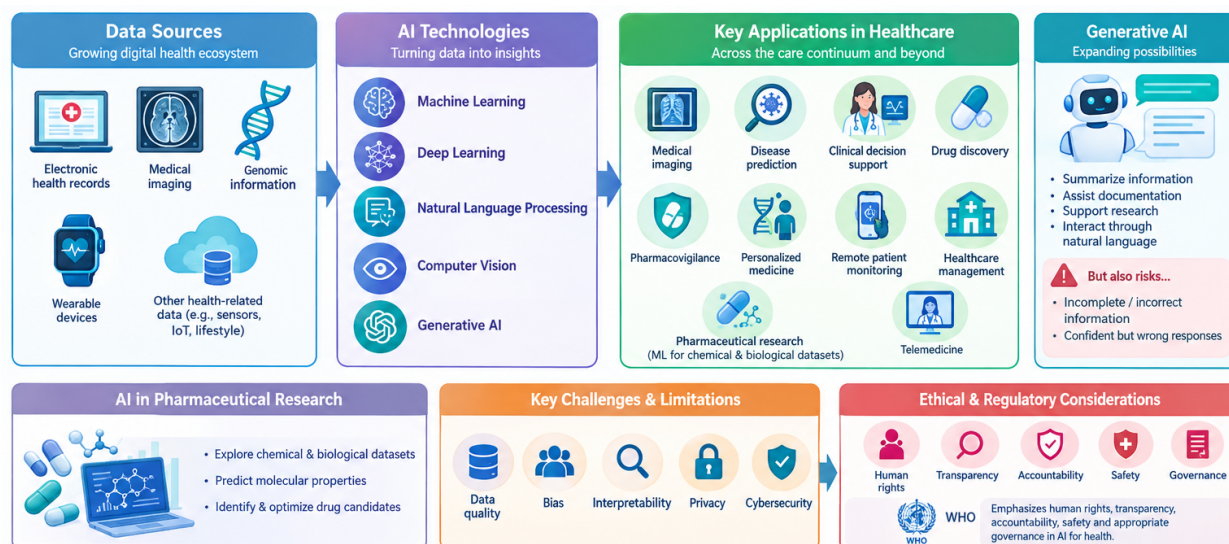
The rapid emergence of generative AI has further broadened the discussion. Large language and multimodal models can summarize information, assist with documentation, support research activities and interact with users through natural language. At the same time, these systems may produce information that is incomplete or factually incorrect, and their apparently confident responses can make such errors difficult to recognize. The World Health Organization has consequently emphasized the importance of human rights, transparency, accountability, safety and appropriate governance in the development and use of AI for health. This review examines the current role of AI in modern healthcare technology, with particular attention to diagnosis, medical imaging, drug discovery, precision medicine, pharmaceutical care, telemedicine, wearable technologies, healthcare management and generative AI. The major limitations and ethical and regulatory concerns are also discussed. Rather than viewing AI as a substitute for healthcare professionals, the review considers a model in which computational systems and healthcare professionals work together, with clinical judgment and patient interests remaining central to healthcare decisions.

**Keywords:** Artificial intelligence; machine learning; deep learning; healthcare technology; generative artificial intelligence; medical imaging; drug discovery; precision medicine; digital health; pharmacovigilance.

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Graphical Abstract

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## 1. Introduction

Healthcare has always been closely linked with technological development. From the introduction of modern diagnostic instruments to electronic health records and advanced imaging systems, new technologies have gradually changed the way diseases are detected and treated. Artificial intelligence represents a different stage of this development because it is not simply another diagnostic or therapeutic instrument. Instead, it provides methods for interpreting and learning from large amounts of information (1).

This distinction has become increasingly important as healthcare data have grown in both volume and complexity. A single patient may generate information from clinical notes, laboratory investigations, imaging studies, prescriptions, genetic testing and wearable devices. At the population level, the amount of information becomes considerably larger. Much of this information is also heterogeneous; some data are numerical, some are visual and some are written in free-text clinical language. Conventional methods can process these data, but doing so efficiently and consistently can be difficult (2).

AI offers one possible approach to this problem. Machine-learning systems can identify patterns within datasets, while deep-learning methods can handle highly complex information such as medical images. Natural language processing can be used to extract information from clinical documents, and computer-vision techniques can analyze visual data. More recently, generative AI has introduced systems capable of producing text, images and other forms of content in response to user instructions (3).

The growing interest in AI is reflected in international health policy. The World Health

Organization identifies applications of AI across diagnosis, clinical care, drug development, disease surveillance and health-system management. At the same time, it emphasizes that the adoption of AI must address safety, equity, governance and ethical considerations.

The development of generative AI has made this discussion even more relevant. WHO's guidance on large multimodal models describes possible applications in diagnosis and clinical care, administrative work, medical education, scientific research and drug development, while also noting the risks of false, incomplete or biased outputs.

It is therefore difficult to discuss the impact of AI simply in terms of whether the technology is "good" or "bad" for healthcare. Its value depends on the task, the quality of the underlying data, the way the system is validated and the environment in which it is used. An algorithm that performs well under controlled research conditions may not necessarily produce the same results when introduced into routine clinical practice (4).

This review discusses these developments from a healthcare and pharmaceutical perspective. Particular attention is given not only to the applications of AI but also to the limitations that need to be considered before such technologies are adopted on a wider scale (5).

## 2. Artificial Intelligence: From Computational Concept to Healthcare Technology

Artificial intelligence is commonly described as the ability of computational systems to perform tasks associated with aspects of human intelligence, such as recognizing patterns, interpreting information, generating predictions and processing language. In practical healthcare applications, however, AI is not a single technology. It represents a collection of

computational approaches that differ in their underlying methods and intended uses (6). Machine learning is one of the most important components. Rather than relying entirely on explicitly programmed rules, machine-learning algorithms learn relationships from data. Depending on the type of problem, supervised, unsupervised or reinforcement-learning approaches may be used. Deep learning represents a further development in machine learning and uses multilayer neural networks to identify increasingly complex patterns. Its application to medical imaging has attracted considerable attention because images contain information that can be difficult to quantify manually. Natural language processing has a different role. Healthcare generates a large amount of information in the form of clinical notes, reports, prescriptions and scientific literature. NLP methods can help convert this unstructured information into a form that can be searched, classified or analyzed computationally. Generative AI has introduced another layer to the field. Instead of only classifying or predicting information, generative systems can produce new text, images or other outputs. Large language models are particularly relevant to healthcare because they can interact with users using natural language (7). These technologies should not, however, be treated as interchangeable. Their performance, limitations and appropriate uses differ considerably. A model developed for image classification, for example, cannot automatically be assumed to be suitable for clinical conversation or drug discovery (8).

**Table 1. AI Technologies and Their Applications in Healthcare**

| AI Technology                            | Major Healthcare Applications                                                                                         |
|------------------------------------------|-----------------------------------------------------------------------------------------------------------------------|
| <b>Machine Learning (ML)</b>             | Disease prediction, risk assessment, clinical decision support, patient outcome prediction                            |
| <b>Deep Learning (DL)</b>                | Medical image analysis, disease classification, pattern recognition, automated diagnosis                              |
| <b>Natural Language Processing (NLP)</b> | Clinical documentation, extraction of information from medical records, clinical text analysis, patient communication |
| <b>Computer Vision</b>                   | Radiological image interpretation, pathology analysis, lesion detection, surgical image analysis                      |

|                                                  |                                                                                                                          |
|--------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------|
| <b>Generative AI</b>                             | Clinical content generation, patient education, medical documentation, research assistance, drug-development support     |
| <b>Large Language Models (LLMs)</b>              | Medical question answering, summarization of clinical information, healthcare communication, decision-support assistance |
| <b>Expert Systems</b>                            | Rule-based diagnosis, clinical decision support, treatment recommendations                                               |
| <b>Reinforcement Learning (RL)</b>               | Treatment optimization, adaptive therapy, resource allocation, personalized intervention strategies                      |
| <b>Robotic AI</b>                                | Robot-assisted surgery, rehabilitation, precision procedures, hospital automation                                        |
| <b>Predictive Analytics</b>                      | Disease-risk prediction, hospital readmission prediction, patient deterioration monitoring, resource planning            |
| <b>Speech Recognition</b>                        | Voice-based clinical documentation, medical transcription, hands-free healthcare interaction                             |
| <b>AI-enabled Computer-Aided Detection (CAD)</b> | Detection and classification of abnormalities in medical images, including tumors and lesions                            |
| <b>AI in Wearable Devices</b>                    | Continuous monitoring of heart rate, activity, sleep, glucose and other physiological parameters                         |
| <b>AI with Internet of Medical Things (IoMT)</b> | Remote patient monitoring, connected medical devices, real-time data analysis and alerts                                 |
| <b>AI in Drug Discovery</b>                      | Target identification, virtual screening, molecular design, toxicity prediction, drug repurposing                        |
| <b>AI in Pharmacovigilance</b>                   | Adverse drug reaction detection, signal identification, safety-data analysis and monitoring                              |
| <b>AI in Personalized Medicine</b>               | Patient stratification, treatment selection, biomarker analysis and individualized therapy                               |
| <b>AI in Healthcare Management</b>               | Hospital workflow optimization, appointment                                                                              |

|  |                                                            |
|--|------------------------------------------------------------|
|  | scheduling, resource allocation, administrative automation |
|--|------------------------------------------------------------|

### 3. Artificial Intelligence in Disease Diagnosis

Diagnosis is among the areas in which AI has received considerable research attention. The basic attraction is relatively straightforward: healthcare professionals must often interpret large amounts of information within a limited period, and AI can assist by identifying patterns that may otherwise be difficult to recognize.

AI-based diagnostic systems have been investigated for cardiovascular diseases, cancers, neurological disorders, ophthalmic diseases, infectious diseases and several other conditions. Depending on the application, an AI system may classify an image, estimate disease risk, identify a possible abnormality or provide information that can be considered alongside other clinical findings.

Medical imaging provides a useful example. An imaging study may contain hundreds or thousands of individual features, and deep-learning systems can examine these features systematically. The resulting output may assist a radiologist or other healthcare professional in prioritizing examinations or identifying areas requiring closer examination.

Importantly, the role of AI in diagnosis should not be reduced to the question of whether an algorithm is more accurate than a clinician. Diagnostic performance in actual practice depends on much more than an algorithm's test accuracy. Patient characteristics, prevalence of disease, quality of the imaging or laboratory data, workflow and the experience of the healthcare professional can all influence the final outcome.

For this reason, clinical validation remains essential. An AI model that performs well in a carefully selected research dataset may behave differently when exposed to patients from another hospital or geographic region (9-15).

### 4. AI in Medical Imaging

Medical imaging has become one of the most established areas of artificial intelligence application in healthcare. AI-based methods are being explored and implemented in radiology, pathology, ophthalmology, dermatology and other specialties where medical images play an important role in diagnosis and assessment. These systems can assist with tasks such as classifying images, detecting abnormalities, identifying and segmenting anatomical structures, measuring disease-related features and prioritizing examinations that may require urgent attention. In clinical practice, AI is therefore increasingly being considered as a support tool for image interpretation rather than simply as an experimental technology (16-18).

The growing use of AI in medical imaging is also reflected in the regulatory landscape. The U.S. Food and Drug Administration (FDA) maintains a publicly available list of AI-enabled medical devices that have been authorized for marketing in the United States. The list includes devices used in areas such as radiology, ultrasound and neurology, among others, although the FDA notes that it is updated periodically and is not intended to include every AI-enabled medical device. The presence of these authorized devices indicates that AI has moved beyond laboratory research into practical healthcare applications. However, regulatory authorization should not be interpreted as evidence that all AI systems will perform in the same way across different clinical environments. Their performance depends on factors such as intended use, patient population, imaging equipment and the conditions under which the system was developed and evaluated.

Another important consideration is dataset shift. An algorithm trained using images from a particular hospital, imaging device or patient population may encounter different image characteristics when introduced into another setting. Such differences can affect its performance and may lead to variations in diagnostic results. For this reason, external validation and continued performance monitoring are important after implementation, particularly when AI systems are used to support clinical decisions (19).

### 5. Artificial Intelligence in Drug Discovery and Development

The pharmaceutical industry presents a particularly interesting environment for AI because drug discovery involves large amounts of chemical, biological and clinical information. Identifying a promising molecule is only one step in a long development pathway, and failure can occur at several stages.

Machine learning can be applied to tasks such as molecular property prediction, virtual screening, identification of potential drug-target interactions, toxicity prediction and lead optimization. Large datasets containing information about compounds and biological activity have made these approaches increasingly feasible.

A 2024 perspective in *Nature Chemical Biology* described machine learning as a potential tool for augmenting traditional drug-development processes, particularly as large chemical and biological datasets become increasingly available.

The potential advantage is not simply speed. Computational approaches can examine chemical spaces that would be difficult to explore experimentally in their entirety. AI-based methods may help researchers narrow the number of compounds that require laboratory investigation.

However, enthusiasm surrounding AI drug discovery needs to be balanced with evidence. Computational prediction does not establish biological activity, safety or clinical efficacy. As noted in *Nature Reviews Drug Discovery*, there remains a substantial gap between promising computational approaches and the rigorous experimental validation required to demonstrate useful drug-discovery outcomes.

The likely contribution of AI is therefore best viewed as an extension of the drug-discovery toolbox rather than a replacement for medicinal chemistry, pharmacology, toxicology and clinical research (20-23).

#### 6. AI in Pharmaceutical Sciences and Pharmacy Practice

The application of AI does not end when a drug reaches the market. Pharmacy and pharmaceutical care generate several types of information that may be suitable for computational analysis.

Potential applications include medication reconciliation, identification of drug interactions, medication-use review, pharmacovigilance, adherence monitoring and clinical decision support.

Pharmacovigilance is particularly relevant. Traditional safety monitoring depends heavily on spontaneous reports, literature surveillance and other sources of post-marketing information. AI and natural language processing may help screen large volumes of reports and literature for possible safety signals.

There is also potential for AI to support patient counselling. A conversational system may provide general information about dosage schedules, administration instructions or medication precautions. However, patient-specific advice can involve factors that are not available to an AI system, including complete medication history, comorbidities, clinical examination and treatment goals. Pharmacist or physician oversight therefore remains important (24-26).

**Table 2. Applications of AI Across Pharmaceutical Research and Healthcare**

| Area                     | Application of AI                    | Potential Contribution                                                           |
|--------------------------|--------------------------------------|----------------------------------------------------------------------------------|
| <b>Drug Discovery</b>    | Target identification and validation | Identification of potential therapeutic targets from complex biological datasets |
| <b>Virtual Screening</b> | Screening of large                   | Prioritization of compounds                                                      |

|                                |                                                                            |                                                                        |
|--------------------------------|----------------------------------------------------------------------------|------------------------------------------------------------------------|
|                                | compound libraries                                                         | for experimental evaluation                                            |
| <b>Molecular Design</b>        | Prediction and generation of candidate molecules                           | Support for lead identification and optimization                       |
| <b>Drug-Target Interaction</b> | Prediction of molecular interactions                                       | Identification of potentially active drug candidates                   |
| <b>ADMET Prediction</b>        | Prediction of absorption, distribution, metabolism, excretion and toxicity | Early identification of compounds with unfavorable properties          |
| <b>Lead Optimization</b>       | Prediction of molecular properties and activity                            | Refinement of promising drug candidates                                |
| <b>Drug Repurposing</b>        | Analysis of existing drugs and disease-related datasets                    | Identification of potential new therapeutic uses                       |
| <b>Formulation Development</b> | Modeling formulation variables and product characteristics                 | Support for formulation optimization and experimental design           |
| <b>Pharmaceutical Analysis</b> | Pattern recognition and analytical-data interpretation                     | Improved analysis of complex pharmaceutical datasets                   |
| <b>Pharmacovigilance</b>       | Detection and analysis of adverse drug reactions                           | Support for identification of potential safety signals                 |
| <b>Medication Management</b>   | Medication reconciliation and interaction screening                        | Reduction of medication-related problems and support for safer therapy |
| <b>Patient Counselling</b>     | AI-assisted medication information and communication                       | Support for patient education and adherence                            |
| <b>Personalized</b>            | Integration of                                                             | Support for                                                            |

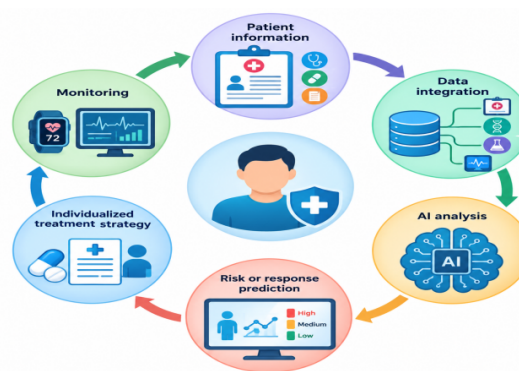
|                                  |                                                                |                                                                |
|----------------------------------|----------------------------------------------------------------|----------------------------------------------------------------|
| <b>Medicine</b>                  | clinical, genomic and patient-specific data                    | individualized treatment selection                             |
| <b>Clinical Decision Support</b> | Risk prediction and clinical data analysis                     | Assistance in evidence-informed clinical decision-making       |
| <b>Electronic Health Records</b> | Extraction and summarization of clinical information           | Improved accessibility and organization of patient information |
| <b>Telemedicine</b>              | AI-assisted symptom assessment and remote consultation support | Support for remote healthcare delivery                         |
| <b>Remote Patient Monitoring</b> | Analysis of physiological and wearable-device data             | Early identification of potentially abnormal changes           |
| <b>Wearable Technologies</b>     | Continuous analysis of physiological parameters                | Support for individualized health monitoring                   |
| <b>Healthcare Management</b>     | Resource allocation, scheduling and workflow analysis          | Improved operational efficiency and healthcare planning        |

For pharmaceutical sciences, AI may also become increasingly relevant to formulation development, drug-delivery research and pharmaceutical analysis. Computational models can be used to investigate relationships between formulation variables and product characteristics, although experimental confirmation remains necessary (27).

### 7. AI and Personalized Medicine

The concept of personalized medicine is based on the recognition that patients with the same diagnosis do not necessarily respond to treatment in the same way. Differences in genetics, age, disease severity, lifestyle, previous treatment and other factors can influence therapeutic outcomes. AI provides a means of integrating several of these variables within a single analytical framework (28-33).

A simplified pathway is:



Genomic medicine is one area where this approach may be particularly valuable. AI can assist in analyzing large genomic datasets and identifying relationships between genetic variations and disease or treatment response.

However, personalized medicine also illustrates one of the central limitations of AI. A prediction is only as useful as the information on which it is based. If important patient characteristics are missing, incorrectly recorded or poorly represented in the training dataset, the resulting prediction may be misleading (34).

### 8. AI in Electronic Health Records

Electronic health records contain both structured and unstructured information. Laboratory values, medication lists and diagnostic codes are relatively structured, whereas clinical notes and reports often contain free text.

Natural language processing and newer language-model-based systems can help extract information from this unstructured material. Possible applications include summarizing records, identifying clinically relevant information and supporting documentation.

Generative AI has received particular attention for clinical documentation. In principle, a system can convert information from a clinical encounter into a structured summary, reducing some of the documentation burden on healthcare professionals.

The important issue, however, is verification. A summary that omits a clinically relevant detail or introduces an incorrect statement can create a new source of risk. For this reason, automated documentation should be reviewed by the responsible healthcare professional before becoming part of the permanent clinical record (35-38).

### 9. Generative AI and Large Language Models

Generative AI has broadened the role of artificial intelligence in healthcare by allowing users to interact with AI systems through natural language. Unlike conventional AI applications that are designed for specific analytical tasks, generative systems can assist with a wider range of activities, including summarizing scientific literature, preparing

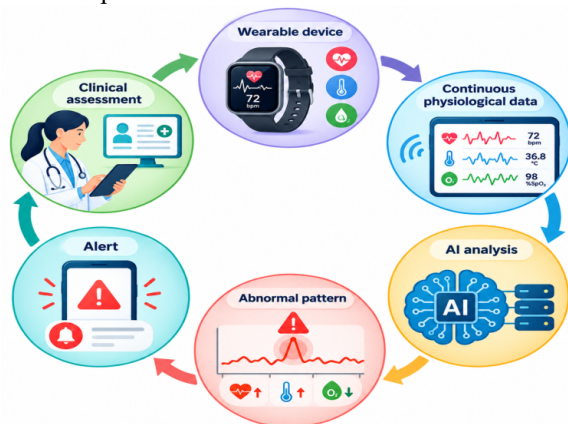
educational materials, supporting clinical documentation, communicating health information to patients, assisting research activities, retrieving information and handling certain administrative tasks. A 2024 scoping review reported applications of generative AI across areas such as diagnosis, treatment and healthcare management, while also identifying concerns related to accuracy, privacy, bias and other potential risks. A major concern with generative AI is that the information produced may appear clear and convincing even when it is incomplete or incorrect. This makes errors particularly difficult to recognize without appropriate verification. The WHO has highlighted that large multimodal models may generate false, inaccurate, biased or incomplete information, which can become especially important when these systems are used in healthcare or for health-related decisions. Therefore, human oversight remains essential. In clinical practice, an AI-generated response should be treated as supportive information rather than an independent clinical judgment, and its accuracy and relevance should be assessed by an appropriately qualified healthcare professional. The ability of a system to produce a convincing response should not, by itself, be considered evidence of clinical reliability (39).

#### 10. AI in Telemedicine and Remote Patient Monitoring

The expansion of telemedicine has created new opportunities for AI-supported healthcare. Remote consultations can generate information about symptoms, medications, vital signs and patient-reported outcomes, while wearable devices can provide continuous physiological data.

AI may help identify patterns within these data and alert healthcare professionals when predefined or learned patterns suggest a possible problem.

For example:



Such systems could be useful for chronic disease management and remote monitoring. However, automated alerts also have limitations. Excessive

false alarms may increase workload rather than reduce it, while a system that fails to identify a clinically important change may create false reassurance.

The usefulness of remote AI therefore depends on appropriate thresholds, validation and integration with a clear clinical response pathway (40).

#### 11. AI, Wearable Devices and the Internet of Medical Things

Wearable devices have changed the nature of health monitoring from occasional measurements to increasingly continuous data collection.

Depending on the device, information may include heart rate, physical activity, sleep patterns, oxygen saturation, temperature and other physiological parameters.

When combined with AI, these data may support individualized monitoring. Instead of comparing every individual with a general population reference, future systems may increasingly learn a person's usual physiological pattern and identify meaningful deviations from that baseline.

The concept is attractive, but several practical issues remain. Consumer devices may differ in sensor quality, algorithms and calibration. Data can also be incomplete because users may remove the device or use it inconsistently. AI-based interpretation therefore requires careful validation before being used for clinical decisions (41).

#### 12. AI in Healthcare Management

Healthcare systems involve substantial administrative work, much of which does not directly involve diagnosis or treatment. Appointment scheduling, resource allocation, patient-flow management and documentation are examples.

AI may help identify patterns in hospital activity and assist administrators with forecasting and planning. This could be useful in situations where demand varies substantially over time.

The attraction of these applications is that they may not require AI to make a clinical decision. Instead, the technology can support organizational processes and reduce repetitive work.

This distinction is important because healthcare AI should not be understood only as a diagnostic technology. Its broader impact may come from the cumulative effect of many smaller improvements across clinical and administrative workflows (42).

**Table 3. Benefits and Limitations of Artificial Intelligence in Healthcare**

| Aspect | Potential Benefits | Major Limitations / Concerns |
|--------|--------------------|------------------------------|
|--------|--------------------|------------------------------|

Impact of Artificial Intelligence on Modern Healthcare Technology: Applications, Challenges and Future Perspectives

|                                  |                                                                                  |                                                                                     |
|----------------------------------|----------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| <b>Diagnosis</b>                 | Supports identification of disease patterns and abnormalities                    | Diagnostic performance may vary across patient populations and clinical settings    |
| <b>Medical Imaging</b>           | Rapid analysis of images and detection of potentially important findings         | Dataset shift, image-quality variation and false-positive or false-negative results |
| <b>Clinical Decision Support</b> | Provides data-driven information to support clinical decisions                   | AI output may be inappropriate when clinical context is incomplete                  |
| <b>Drug Discovery</b>            | Accelerates virtual screening, molecular prediction and lead optimization        | Computational predictions require experimental and clinical validation              |
| <b>Pharmacovigilance</b>         | Helps process large volumes of safety information and identify potential signals | Incomplete, inconsistent or biased safety data may affect signal detection          |
| <b>Personalized Medicine</b>     | Supports integration of patient-specific clinical and genomic information        | Requires high-quality, representative and sufficiently comprehensive patient data   |
| <b>Electronic Health Records</b> | Facilitates information extraction, summarization and organization               | Privacy risks, incomplete records and incorrect automated summaries                 |
| <b>Remote Monitoring</b>         | Enables continuous analysis of physiological and wearable-device data            | Device variability, missing data and excessive false alerts                         |
| <b>Telemedicine</b>              | Supports remote                                                                  | Cannot fully replace                                                                |

|                              |                                                                          |                                                                                     |
|------------------------------|--------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
|                              | assessment, communication and information management                     | physical examination or comprehensive clinical assessment                           |
| <b>Healthcare Management</b> | Supports scheduling, resource planning and workflow optimization         | Poorly designed systems may introduce operational inefficiencies                    |
| <b>Generative AI</b>         | Assists documentation, education, research and communication             | May generate inaccurate, incomplete or fabricated information                       |
| <b>Large Language Models</b> | Enables natural-language interaction and rapid information summarization | Responses may appear convincing despite containing factual errors                   |
| <b>Efficiency</b>            | Automates repetitive and data-intensive tasks                            | Implementation, integration and maintenance can require substantial resources       |
| <b>Data Analysis</b>         | Processes large and complex datasets rapidly                             | Performance depends strongly on data quality and availability                       |
| <b>Equity in Healthcare</b>  | May expand access to certain digital healthcare services                 | Biased training data or unequal access to technology may worsen disparities         |
| <b>Patient Safety</b>        | Can support early detection and clinical monitoring                      | Errors may cause harm when AI outputs are accepted without appropriate verification |
| <b>Healthcare Workforce</b>  | May reduce some repetitive                                               | Inadequate training and poor workflow                                               |

|                            |                                                                              |                                                                                              |
|----------------------------|------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|
|                            | administrative and analytical workload                                       | integration may create additional workload                                                   |
| <b>Transparency</b>        | Some AI systems can provide useful predictive information                    | Complex models may be difficult to interpret or explain                                      |
| <b>Scalability</b>         | Digital AI systems can potentially be deployed across large populations      | Performance may change when systems are transferred to different institutions or populations |
| <b>Continuous Learning</b> | AI systems can potentially incorporate new information and improve over time | Model updates require monitoring, validation and appropriate governance                      |

### 13. Ethical and Regulatory Considerations

The rapid development of AI has created new challenges for healthcare regulation because technological advances are occurring faster than many existing regulatory frameworks. The WHO emphasizes that AI in healthcare should be guided by principles such as safety, transparency, accountability, human autonomy, equity and sustainability. These principles are particularly important when AI contributes to clinical decision-making, where errors or inappropriate outputs may affect patient safety. Data privacy, algorithmic bias, transparency and accountability are also important concerns. AI systems trained on incomplete or unrepresentative datasets may perform differently across patient populations, while complex models may be difficult for healthcare professionals to interpret. Continuous monitoring and validation are therefore necessary after deployment. WHO guidance on large multimodal models also highlights the need for appropriate governance and human oversight, particularly because generative systems may produce inaccurate or incomplete information. Recent WHO guidance on AI-related health research further emphasizes fairness, responsible data governance and protection against unequal distribution of risks and benefits. Therefore, ethical and regulatory considerations should be incorporated throughout the development, validation and use of AI rather than being treated as an issue only after implementation (43-46).

### 14. Current Limitations and Research Gaps

The most important limitation of healthcare AI is perhaps the gap between technical performance and clinical usefulness.

An algorithm can achieve excellent performance on a benchmark dataset and still have limited value in routine practice. The reasons may include differences in patient populations, incomplete information, changes in clinical workflows or difficulties in interpreting the output.

Several research gaps therefore deserve attention.

First, more prospective studies are required. Much of the existing AI literature is based on retrospective datasets, whereas healthcare decisions occur prospectively.

Second, external validation needs greater emphasis. Models should ideally be evaluated across different hospitals, regions and patient populations.

Third, researchers need to report more than accuracy. Sensitivity, specificity, calibration, clinical utility, safety and patient outcomes may all be relevant depending on the intended use.

Finally, the effects of AI on healthcare professionals and patients deserve greater attention. A system that improves diagnostic accuracy but substantially increases clinician workload may not provide the expected overall benefit (47-51).

### 15. Future Perspective

The next stage of healthcare AI is likely to involve greater integration rather than isolated applications. Medical images, electronic records, laboratory results, genomic information and physiological data may increasingly be analyzed together. Multimodal AI is particularly relevant to this development because it is designed to work across more than one type of input.

WHO's guidance on large multimodal models identifies healthcare, scientific research, public health and drug development as areas in which these systems may have important applications, while emphasizing the need for careful governance. In pharmaceutical research, AI may increasingly be combined with high-throughput screening, molecular modeling and experimental platforms. In clinical practice, AI may become more embedded within existing software rather than appearing as a separate application. The likely long-term model is therefore not: Human versus AI, but rather: Healthcare professional + AI + Patient. In this model, computational systems perform data-intensive tasks, while healthcare professionals provide clinical interpretation, contextual understanding and accountability. Patients remain participants in decisions affecting their health. Such a model is likely to be more realistic than the idea of complete automation of healthcare.

### 16. Conclusion

Artificial intelligence is becoming an important part of modern healthcare technology, but its significance should be considered carefully. Its strongest contribution is not necessarily the replacement of existing healthcare practices; rather, it lies in providing new ways of working with information.

Medical imaging, disease prediction, drug discovery, pharmacovigilance, personalized medicine, electronic health records, telemedicine and wearable monitoring are among the areas where AI is already being explored or implemented. Generative AI has further expanded the field by making interaction with computational systems more accessible.

At the same time, the limitations of AI are becoming clearer. Poor-quality data, algorithmic bias, limited external validation, privacy concerns and inaccurate generative outputs can reduce the reliability of these technologies. Regulatory and ethical frameworks are therefore not secondary considerations. They are necessary components of responsible implementation.

For pharmaceutical and healthcare sciences, AI should be viewed as an additional tool that can complement established scientific methods. Computational predictions still require experimental confirmation, and clinical recommendations still require appropriate professional judgment.

The future impact of AI will ultimately depend less on the ability of algorithms to perform isolated tasks and more on how effectively they can be incorporated into real healthcare systems. A responsible approach, based on clinical evidence, human oversight, transparency and equitable access, offers a more realistic pathway toward achieving meaningful benefits from AI in healthcare.

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