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A Review Article On Ai In Healthcare Application And Current Challenge

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Abstract

The rapid integration of Artificial Intelligence (AI) in healthcare has revolutionized medical diagnosis, treatment, and patient care. This comprehensive review provides an in-depth examination of AI's transformative impact on healthcare, encompassing drug discovery, clinical trials, patient care, robotics-assisted surgery, and virtual nurse assistants. The applications of AI in healthcare are vast, with potential benefits including improved diagnostic accuracy, enhanced patient outcomes, and reduced healthcare costs. However, AI's limitations and challenges in healthcare are also addressed, including ethical concerns, data bias, reliability and safety issues, transparency and accountability challenges, effects on patient trust, and data privacy and security risks. The review highlights the need for interdisciplinary collaboration, regulatory frameworks, and emerging trends such as Explainable AI and Edge AI.By exploring AI's applications and challenges in healthcare, this review informs healthcare professionals, policymakers, and researchers on the future directions of AI in healthcare. The article concludes with recommendations for addressing current challenges, ensuring AI's safe and effective integration into healthcare, and optimizing its benefits for improved patient outcomes.

Keywords: artificial intelligence, ethics, governance, healthcare

Introduction

The integration of Artificial Intelligence (AI) in healthcare is revolutionizing medical diagnosis, treatment, and patient care. AI's transformative impact extends across various domains, including drug discovery, clinical trials, patient care, robotics-assisted surgery, and virtual nurse assistants. AI-driven innovations have improved disease diagnosis, personalized treatment planning, and patient engagement, demonstrating significant potential for enhanced healthcare delivery. However, despite AI's benefits, challenges persist, including ethical concerns, data bias, reliability and safety issues, and effects on patient trust and healthcare professionals. Addressing these challenges is crucial to ensure AI's safe and effective integration into healthcare. This review article provides a comprehensive overview of AI's applications and challenges in healthcare, informing healthcare professionals, policymakers, and researchers. We examine AI's successes and limitations, highlighting future directions and emerging trends. By exploring AI's potential and challenges, this review aims to contribute to the ongoing discussion on optimizing AI's benefits for improved patient outcomes and enhanced healthcare delivery.

Ai in clinical trials

Clinical trials continue to be the gold standard for ensuring the development of safe and effective drugs, despite the significant challenges and investments required. The application of artificial intelligence (AI) is a promising strategy to improve the efficiency and outcomes of these trials[1,2]. AI tools can assist in designing trials by reducing participant numbers and trial duration, and by automating processes such as participant eligibility analysis, which helps match participants with trials more effectively. These tools also simplify the trial search process. Additionally, AI-powered sensors and wearable devices enable better monitoring during trials. AI is also useful for statistical analysis, addressing issues like missing data or visits, which was especially critical during the COVID-19 pandemic 3,4].

The Transformative Role of AI in Optimizing Clinical Trials

Predicting probability of trials success : AI algorithms can predict which participants will progress quickly and reach trial endpoints sooner, thereby potentially shortening trial duration[5]. Machine learning (ML) algorithms show promise in detecting diseases early and improving overall trial success rates[6]. AI can also predict molecular properties, drug sensitivity, and potential toxicity early in the research process, thus reducing the likelihood of failure in later trial phases, and improving the design of Phase II and III trials to increase the chances of regulatory approval[7,8]. This has a significant positive impact on both human and financial resources, as well as on ensuring the safety of participants and the public perception of clinical trials[7,9].

Reshaping Clinical Trial Design: AI plays a transformative role in clinical trial design and drug discovery. Here are some key points:

Enhanced Hypothesis Generation: AI accelerates the generation and analysis of hypotheses, offering a deeper understanding of disease progression.

Drug Discovery: AI improves cohort selection through biomarker validation and protocol optimization, enhancing drug discovery processes.

Monitoring and Adherence: AI helps in better monitoring of patient adherence to trial protocols.

Endpoint Selection: AI assists in selecting trial endpoints, ensuring more relevant and reliable outcomes[2,9].

AI in Patient Recruitment: AI also improves patient recruitment by integrating various data types—such as demographics, lab results, and genomic data—making it easier to match patients with trials based on complex criteria[1,10,11]. AI-based systems can automate trial recommendations, leading to more diverse and inclusive trial participation[12]. Additionally, AI-based matching engines have been shown to improve patient awareness and participation in trials, such as in HIV clinical trials[13]. Standardized language in eligibility criteria is key for the success of AI in trial recruitment, as it ensures accurate interpretation by AI systems[14,15].

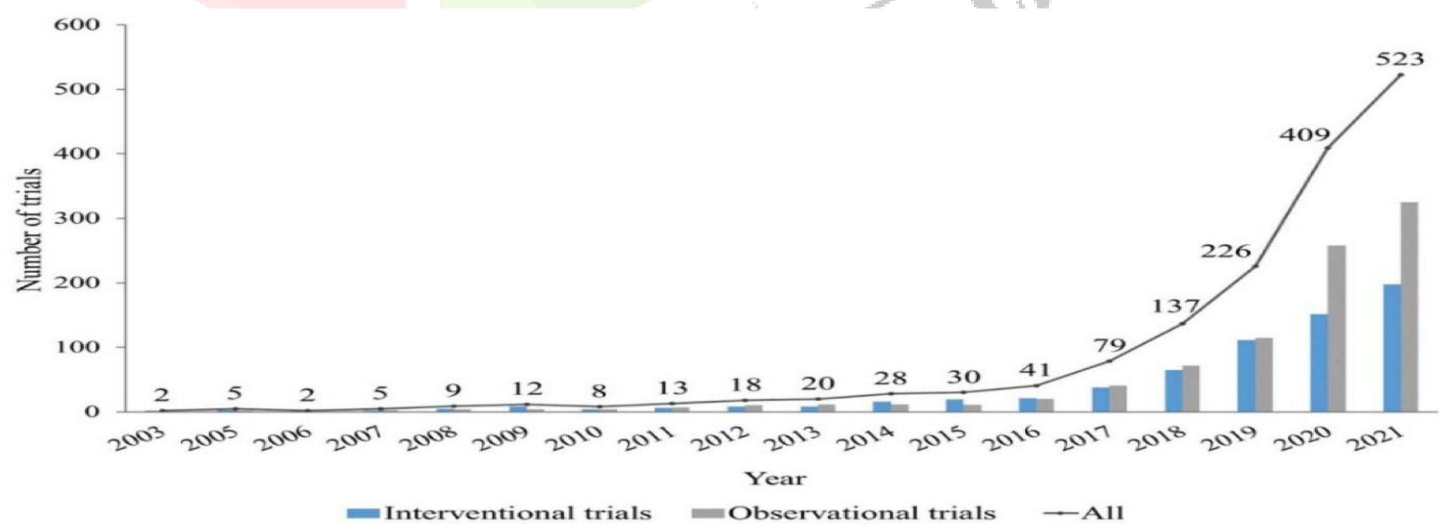

Figure 1. Growth of AI-Driven Healthcare Trials (2003-2021)

This graph illustrates the increasing number of healthcare trials involving artificial intelligence (AI) from 2003 to 2021. The blue bars represent "Interventional trials," where researchers introduce AI-based treatments or interventions. The gray bars show "Observational trials," where AI is used to observe and collect data without intervention. The black line represents the total number of trials (both interventional and observational). The number of trials remained relatively low until 2016, after which there was a rapid rise, particularly in interventional trials. By 2021, the total number of AI-related trials reached 523, reflecting the growing role of AI in healthcare research.[16]

Digital Health Technologies (DHTs) in Trial Conduct: AI-equipped video capture devices provide a reliable way to confirm medication adherence, offering a practical alternative to in-person observation. Automated data collection through wearable devices enhances real-time monitoring of trial participants, improving safety and response times, especially in those with severe conditions. These technologies are particularly useful in psychiatric and neurological trials[17,18,19].

AI in Medical Image Analysis: AI tools are increasingly used to automate the analysis of medical images in clinical trials, reducing manual effort, improving efficiency, and potentially increasing accuracy[20].

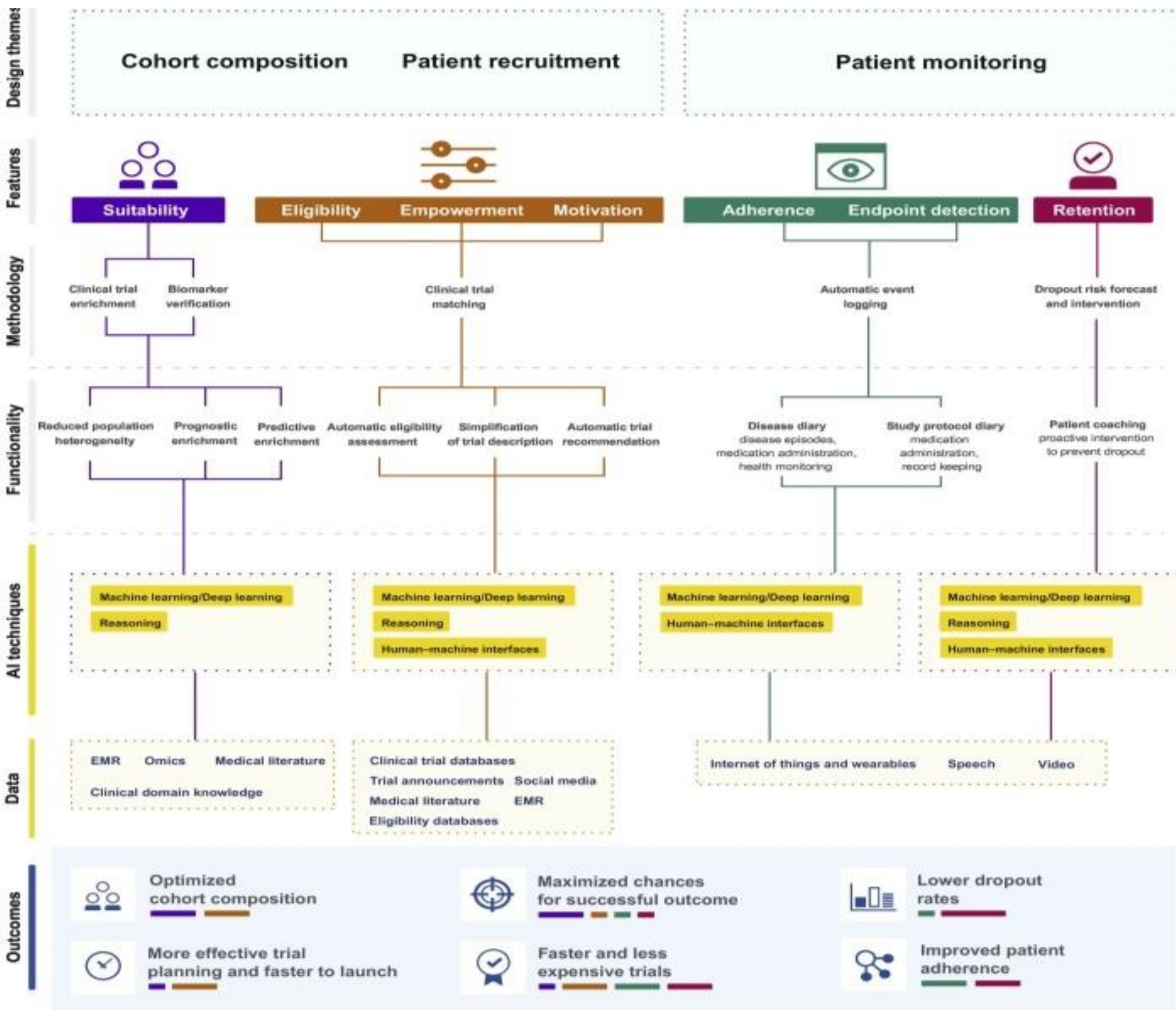

Fig 2. AI for clinical trials design

This figure presents a comprehensive framework for clinical trials, depicting the key elements of cohort composition, patient recruitment, and patient monitoring. It highlights the various factors, technological tools, and approaches involved in optimizing trial design, maximizing chances of successful outcomes, and improving patient adherence to reduce dropout rates.

Role of AI in Drug Discovery:

Artificial intelligence (AI) is transforming drug discovery by making the process faster, more accurate, and efficient. Traditionally, drug discovery is complex and lengthy, relying on methods like trial-and-error and high-throughput screening. AI methods, such as machine learning (ML) and natural language processing, enable the analysis of vast datasets, accelerating the discovery of new drugs [21]. Recent studies show how deep learning (DL) can predict the efficacy of drug compounds with accuracy, enhancing the drug development process [22]. AI is also used to predict the toxicity of drug candidates, helping researchers avoid pursuing harmful compounds [23]. These advancements highlight the significant potential of AI to make drug discovery both faster and more effective.

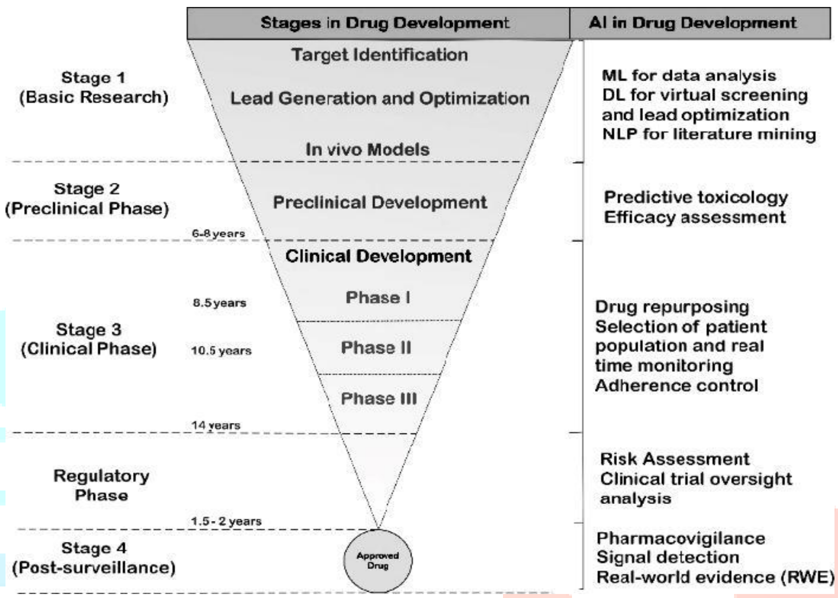

fig.3 Drug development process showing application of AI at each stage [3].

This figure provides an overview of the drug development process and highlights how Artificial intelligence (AI) can be applied at each stage of drug development process involves several stages: basic research, preclinical testing, clinical trials, regulatory review, and post-market surveillance. AI plays a crucial role throughout these stages by aiding in data analysis, virtual screening, and literature mining during basic research; predicting toxicity and efficacy in preclinical testing; supporting patient selection, monitoring, and drug repurposing in clinical trials; facilitating risk assessment in the regulatory phase; and enhancing pharmacovigilance and real-world evidence analysis post-approval. This integration of AI improves efficiency, reduces costs, and accelerates the drug discovery pipeline.

Predicting Drug Efficacy and Toxicity with Machine Learning

ML techniques help scientists analyze large datasets to identify patterns that might not be immediately obvious. For instance, a deep learning algorithm was trained on known drug compounds and their biological effects, allowing it to predict the activity of new compounds accurately [24]. Similarly, ML has been used to predict the toxicity of drug candidates by comparing them with data from toxic and non-toxic compounds [25].

AI also plays a vital role in identifying drug-drug interactions, which occur when multiple drugs are used simultaneously. These interactions can alter a drug’s effect or cause harmful side effects. Machine learning models can predict interactions between new drug pairs, which is crucial for personalized medicine, where treatments are tailored to a patient’s unique profile [26].

AI's Impact on Drug Discovery Efficiency and Cost Savings

AI has a transformative impact on drug discovery, particularly in the design of new drug compounds. Traditional methods involve modifying existing compounds, which is time-consuming. In contrast, AI techniques can rapidly design new molecules with desirable traits, such as better solubility and activity. For example, a deep learning model was trained to propose new therapeutic molecules based on known drugs [27]. Another major breakthrough is AlphaFold, developed by DeepMind, which uses AI to predict protein structures, revolutionizing personalized medicine and drug design [28]. AI-driven methods, combined with molecular dynamics simulations, improve the speed and accuracy of drug design [29].

Case Studies of AI in Drug Discovery

Several successful AI-driven drug discovery efforts have been documented. Gupta et al. used a deep learning algorithm to discover new compounds for cancer treatment, based on a dataset of cancer-related molecules [30]. Similarly, machine learning methods were applied to identify small-molecule inhibitors of the protein MEK, a challenging target in cancer therapy [31]. Another example includes the identification of beta-secretase inhibitors, a protein involved in Alzheimer's disease, using AI [32].

Challenges and Limitations of AI in Drug Discovery

Despite AI's potential, there are challenges. AI models need large amounts of high-quality data, but such data can be limited, inconsistent, or inaccurate, reducing the effectiveness of AI predictions [33,34]. Ethical concerns also arise regarding fairness and bias in AI, especially if the training data are not representative of diverse populations [35,36,37]. It's important to use AI ethically in drug discovery to avoid biased outcomes [38]. Moreover, AI tools complement, rather than replace, traditional methods and human expertise. While AI offers predictions, human validation and interpretation remain essential [39]. By integrating AI with traditional methods, researchers can combine AI's speed and predictive power with expert judgment [40,41].

AI in Patient Monitoring

Recent advancements technology in AI have fueled interest in continuous patient monitoring systems that track vital signs such as heart rate and breathing rate. These systems are particularly beneficial for elderly or chronically ill patients in hospitals, at home, or while on the move. Artificial intelligence (AI) is playing a key role in functions such as disease diagnosis, outcome prediction, medical imaging, and drug development. AI has the potential to improve treatment outcomes and refine decision-making by analyzing vast amounts of healthcare data. However, the increased use of AI also introduces new challenges. Additionally, AI has improved diagnostic imaging in procedures like CT scans, MRIs, and X-rays, enhancing patient safety and clinical effectiveness [42].

Technological Architectures for Remote Patient Monitoring

Video-Based Monitoring

Telehealth enables patients to connect with healthcare professionals through audio or video calls using smart devices. Reports show that telehealth use has surged over the last decade. It covers applications like mental health support, pain management, blood pressure and glucose monitoring, stroke management, and diagnostic services for conditions such as skin and eye diseases. The COVID-19 pandemic has accelerated the use of telehealth to ensure the safety of patients and clinicians. AI methods, including machine learning and image processing, have improved telehealth monitoring by tracking vital signs like heart rate, respiratory rate, oxygen levels, cough analysis, and blood pressure [43].

IoT-Enabled Monitoring Systems

IoT-based real-time remote patient monitoring (RPM) systems help achieve continuous monitoring. These systems are mostly designed for use in hospitals or private homes, but some can function well in both environments [44].

Cloud Computing

Cloud computing plays an important role in RPM systems by managing the large amounts of data generated by IoT devices. This data is stored and shared among healthcare providers, enabling better trend analysis and patient care [45].

Fog and Edge Computing

Fog computing extends cloud computing by bringing services closer to IoT devices. While IoT and cloud computing advancements have improved real-time monitoring of patient vital signs, they have also introduced challenges like security risks, performance issues, delays, and network failures [46].

Applications of AI in Patient Monitoring Systems

Vital Signs Monitoring

Continuous health monitoring systems use connected smartwatches to track vital signs. These systems send the collected data to administrators, who analyze it using Support Vector Machine (SVM) models. One system demonstrated a 90% accuracy rate and a recall rate of 99%, detecting cardiovascular diseases in 99% of patients. This shows the potential of smartwatches in real-time health monitoring and clinical decision support [48].Remote patient monitoring (RPM) systems designed to detect ECG signals use a decision tree ensemble classifier trained with the CatBoost learning kit. This system achieved a sensitivity of 99.61%, a specificity of 99.64%, and an accuracy of 99.62%. It processed 30 seconds of ECG data in just 0.5 seconds, highlighting its efficiency in real-time monitoring [47].The IoT-based wearable 12-lead ECG SmartVest uses an SVM model to evaluate signal quality. This system achieved an average accuracy of 97.9% for high-quality ECG segments and 96.4% for low-quality segments, improving the reliability of the monitoring process [46].

Chronic Disease Monitoring

Machine learning models such as Logistic Regression, XGBoost, and Random Forest have demonstrated high accuracy in predicting diabetes, mental health outcomes, emergency events, and ICU mortality [49, 50, 51].

Facial and Emotional Recognition

AI can assess a patient's emotions by recognizing facial expressions. An advanced patient monitoring system uses facial recognition algorithms, along with heartbeat and temperature sensors, to monitor emotional states and heart rates [52].

This table highlights advanced health monitoring applications using machine learning models, demonstrating their effectiveness in tracking vital signs and detecting cardiovascular conditions in real time.

Table 1.Overview of Machine Learning Applications in Wearable Health Monitoring Systems

Machine Learning Model	Accuracy	Recall/Sensitivity	Specificity	Processing Time	Description
Support Vector Machine (SVM)	90%	99%	N/A	N/A	Tracks vital signs, detects cardiovascular diseases with real-time monitoring for clinical support.
Decision Tree Ensemble (CatBoost)	99.62%	99.61%	99.64%	0.5 seconds	Detects ECG signals with high sensitivity and specificity, processing data efficiently for real-time monitoring.
Support Vector Machine (SVM)	97.9% (High Quality), 96.4% (Low Quality)	N/A	N/A	N/A	Evaluates ECG signal quality in real time, enhancing reliability for wearable health monitoring.

Each application leverages machine learning for accurate, efficient, and reliable health monitoring, supporting timely medical interventions and enhancing patient care.

Robotic-Assisted Surgical Systems (RASS)

Robotic-Assisted Surgical Systems (RASS) are defined as "Medical Electrical Equipment/Systems that use a Programmable Electrical Medical System to help with the positioning or control of robotic surgical tools" [53].

Role of Robotic-Assisted Surgeries in Public Health :

1. Minimally invasive surgery is popular among patients, doctors, and insurance companies because it offers several benefits. These include smaller cuts, a lower risk of infection, shorter hospital stays (or none at all), and faster recovery. Research shows that laparoscopic surgeries lead to quicker return to work, less pain, better cosmetic results, and improved immune function after surgery [54,55,56].
2. Robotic surgery offers a high level of precision, allowing robots to perform delicate tasks that can be challenging for human surgeons. This precision improves surgical outcomes, reduces errors, and minimizes complications. As a result, there is a decreased need for follow-up care, which benefits public health. Various robotic systems have been integrated into surgery, with different platforms for specific procedures. Technological advancements, such as vibration control, enhanced wrist movement, motion scaling, and improved ergonomics, have led to better outcomes compared to traditional laparoscopic surgery [57].
3. Minimally invasive surgery (MIS) also leads to less blood loss compared to open surgery and helps preserve important proteins like albumin and globulin, which are vital for the immune system to prevent

infections. Robotic surgery further reduces blood loss, minimizing the need for transfusions, and helps preserve the limited supply of donated blood, which is essential for public health [58]

4. Cost Efficiency and Access to Robotic Surgery
   Robotic surgery can lower long-term healthcare costs by increasing surgical efficiency and reducing emergency room and office visits [59].
5. Telesurgery: Expanding Surgical Access
   Telesurgery, also known as remote or master-slave technology, has significantly progressed in medical procedures. However, rural areas often lack surgical expertise, causing longer travel times and treatment delays for patients, including cancer patients [60]. Telesurgery addresses these challenges by allowing surgeons to operate remotely, reducing travel time and improving access to care [61]. It also enables experienced surgeons to mentor less experienced ones in real-time, enhancing surgical outcomes. This technology can extend surgical care to remote locations, such as rural areas, battlefields, or even space [62].

Challenges of Robotic-Assisted Surgery in Public Health

Financial viability is a major consideration when adopting robotic surgery. Healthcare providers must weigh the high cost of new technologies against the need to deliver high-quality care at reduced costs. Although robotic surgery can improve precision and shorten recovery times, its availability is limited in low-income countries due to financial constraints. The initial investment in robotic systems is still high, slowing adoption despite the potential benefits over traditional laparoscopic methods. Concerns about the cost-effectiveness of robotic-assisted surgery compared to conventional techniques further restrict its widespread use.[62].

Virtual Nursing Assistants

Virtual nursing assistants are not humanoid robots; they are apps, chatbots, and AI-driven platforms that assist with patient care. These assistants collect health data from patients daily, allowing doctors to receive updates without in-person visits. They use wireless devices and continuous tracking to monitor patient health and detect potential problems based on symptoms. Their duties include sending health reports to doctors, scheduling appointments, and maintaining electronic medical records (EMRs) [63].

Tasks and Duties of Virtual Nursing Assistants

Maintaining Electronic Medical Records:

Virtual nursing assistants can manage and update medical transcriptions through electronic medical records (EMRs), which serve as digital charts. EMRs contain vital information, including treatment plans and diagnostic test results. The use of this technology ensures patient records are accurate and up-to-date, reducing the risk of errors common in traditional paper records. This transition supports better patient care and streamlines administrative processes [64].

Helping with Personalized Medicine:

Machine learning systems analyze patient data, including genetic information, lifestyle choices, and medical history, to create highly personalized medication plans.

Enhancing Patient Engagement and Support:

Virtual nursing assistants help with scheduling appointments, streamlining insurance claims, and providing healthcare education.

24/7 Accessibility and Its Impact on Patient Care:

They perform various remote tasks such as:

- Scheduling appointments
- Registering patients
- Verifying insurance
- Coordinating medication refills
- Following up after visits

Personalized Communication with Patients:
Effective communication is vital for building trust and fostering relationships. Personalized communication helps address patients' specific needs and preferences, increasing satisfaction, improving adherence to treatment plans, and enhancing health outcomes. Understanding each patient's unique situation encourages active participation in their healthcare journey.

Looking Ahead: The Future of Virtual Nursing

The future of virtual nursing assistants looks promising, especially with recent trends in the healthcare industry. The COVID-19 pandemic has significantly increased the use of virtual care and telehealth services, leading to a 41% rise in the demand for virtual medical aides.

Some key statistics include: Telehealth visits reached $26 million for primary care specialists.Mental health specialists conducted $10.1 million in telehealth visits.This shift toward virtual care shows that virtual nursing assistants can deliver high-quality healthcare remotely. Their growing popularity is backed by significant investments in digital health technologies, which reached a record $57.2 billion in 2021, according to the State of Digital Health 2021 Report from CB Insight.[64]

Limits of AI

Ethical and social issues - reliability and safety

The trustworthiness of medical AI depends on its safety, reliability, and respect for human rights and values. We took a multidisciplinary approach to examine this trustworthiness at two levels: design and application(fig.1). At the design level, the focus is on the reliability of the technology, which hinges on the quality of data and algorithms. For data, we consider how it is collected, processed, and stored, addressing issues like informed consent, data quality, and privacy. Regarding algorithms, we look at potential flaws, biases, errors, and security issues that can arise. At the application level, the effects of medical AI on human rights and who is responsible for its actions are crucial for its trustworthiness. This includes concerns about personal autonomy and privacy, as well as determining the moral status of AI and accountability. From our analysis, we identified five key factors that influence the trustworthiness of medical AI: data quality, algorithmic bias, opacity, safety and security, and responsibility attribution[65].

Ethical considerations are vital for the responsible use of Explainable AI in healthcare. Here are some key points to consider:

1. **Transparency and Accountability**: AI should be clear and provide understandable reasons for its decisions. This helps healthcare professionals and patients trust the AI and understand its recommendations, avoiding the "black box" issue.
2. **Fairness and Bias Mitigation**: AI trained on biased data can reinforce existing biases, leading to unfair outcomes in healthcare. Ethical implementation of AI requires careful attention to reduce bias during data collection, processing, and training, promoting fairer healthcare practices.
3. **Informed Consent and Human Involvement**: Patients should be informed about how AI is used in their care. Clear communication about the role and risks of AI is essential for obtaining informed consent. Patients should have the option for human explanations to ensure their autonomy is respected.
4. **Patient-Centered Care**: AI should prioritize the well-being of patients, ensuring that AI decisions align with their best interests. It should support healthcare professionals and enhance their decision-making while considering individual patient circumstances.
5. **Continual Evaluation and Improvement**: Ethical AI involves ongoing assessment and enhancement of the system's performance. Regular monitoring and user feedback help identify and fix issues, contributing to better healthcare outcomes.
6. **Professional Responsibility and Education**: Healthcare professionals must understand and appropriately use AI. This includes being aware of AI's limitations and biases while maintaining clinical expertise. Proper training on AI is necessary for responsible usage.

7. **Ethical Frameworks and Guidelines**: Following established ethical principles, like beneficence, non-maleficence, autonomy, and justice, can guide XAI development and use. Ethical guidelines from medical organizations or governmental bodies can help navigate the specific challenges of AI in healthcare [66].

AI systems may perform very well at detecting conditions that are well-known and have plenty of data available for training. However, this method might fall short when it comes to recognizing rare, unusual, or new conditions that don't fit established patterns [67]. Misdiagnoses or missed diagnoses can happen, which may have serious consequences for patient care. For example, an AI tool designed to recommend treatments based on cost-effectiveness can face limitations if its goals aren't carefully set. While cost-effectiveness is important, focusing only on cost might overlook key factors like a patient's health condition, co-morbidities, and overall well-being. If the goals are too narrow, the recommendations might be financially sensible but not medically or ethically appropriate. In drug discovery, it's essential to limit the AI system's exploration space to avoid suggesting harmful compounds. Even though the AI might explore many chemical combinations, it must be programmed to exclude known toxic substances. Patient safety must come first, so the exploration space should be carefully defined from the start. Similarly, with surgical robots, it's vital to set clear boundaries to ensure safe operations. For instance, a surgical robot should only make incisions within specific areas, even if it identifies potential benefits elsewhere. Going outside these limits can risk serious harm, like damaging healthy tissues or organs [68,69].Healthcare AI systems handle a lot of sensitive information, making them appealing targets for cyberattacks. Adversarial testing is important for finding weaknesses in how data is stored, accessed, and transmitted. This testing helps identify areas that need improvement to prevent unauthorized access or data breaches. It also assesses the system's ability to maintain data integrity, ensuring that patient information stays accurate despite potential attacks. Given the sensitive nature of healthcare data and its impact on medical decisions, adversarial testing is essential, not optional. It helps ensure accurate interpretation of medical images and protects vast amounts of patient data. By systematically uncovering and addressing vulnerabilities, adversarial testing can greatly enhance the reliability and security of these critical AI technologies[70].

3.2Transparency and accountability

Transparency in AI means that people can easily understand how an AI system makes decisions. It includes access to and comprehension of the internal processes and outputs of AI models[71].According to the AI-HLEG and WHO, the necessary transparency for establishing trustworthy AI has not yet been achieved. Two earlier studies offered internal assessment frameworks for organizations aiming to evaluate whether their AI tools align with the ethical standards for trustworthy AI[72]. Other studies have created external assessment frameworks designed to qualitatively identify the technical and ethical challenges associated with AI systems from an outside perspective[73,74].However, these frameworks do not specifically evaluate whether the transparency requirements for trustworthy AI are met[75].The primary focus is on transparency, it's important to highlight that AI is closely tied to algorithmic transparency. Although terms like algorithmic transparency and algorithmic decision-making are commonly used in current critical research, we believe there is a need for more nuanced and refined terminology regarding their relationship to AI. This will help clarify the conceptual framework surrounding transparency.[76].

Accountability typically involves the following:

- Demonstrating outcomes, such as providing explanations for decisions
- Ensuring that AI systems are held responsible
- Making fair decisions or addressing unfair outcomes

According to the definition provided by the European Commission's High-Level Expert Group on Artificial Intelligence, accountability encompasses auditability, the minimization and reporting of negative impacts, consideration of trade-offs, and mechanisms for redress[77]. Our primary contribution to the discussion on AI accountability is twofold. First, we explore non-instrumental arguments for accountability based on democratic theory. Second, we differentiate between direct public accountability through public transparency and indirect public accountability through transparency to auditors. We contend that both forms can achieve public accountability. Additionally, we support our conceptual framework by demonstrating its practical relevance; we show that several requirements in 16 guidelines for AI in public administration address the key issues highlighted in our theoretical analysis.[78].The analysis of the guidelines reveals that they can be seen as addressing a broad accountability issue, specifically one arising from technological delegation, rather than an accountability gap tied solely to the features of recent AI techniques. In fact, many non-computational systems and situations present similar accountability challenges that we discuss in relation to AI, indicating that the issues we're examining are not unique to AI.

Furthermore, the debate would benefit from clearer definitions regarding the entitlements of auditors and the objectives of auditing. This clarity is essential for developing ethically meaningful standards against which different auditing methods can be assessed and compared. Thus, the distinctions we introduce can enhance understanding of the goals related to advocating for accountability in AI systems.[79].

Data bias, fairness and equity

Artificial intelligence (AI) has the potential to change many industries and enhance people's lives in various ways. However, a significant challenge in developing and using AI is bias. Bias refers to systematic errors in decision-making that can lead to unfair results. In AI, bias can come from several sources, such as how data is collected, how algorithms are designed, and how humans interpret outcomes.

Machine learning models, a type of AI, can learn and perpetuate existing biases in the training data, leading to unfair or discriminatory results. This section will look at the different sources of bias in AI—data bias, algorithmic bias, and user bias—and provide real-world examples of their effects[80]. Bias in AI can originate from various stages of the machine learning process, including data collection, algorithm design, and user interactions. This survey will explore the different sources of bias in AI, providing examples of data bias, algorithmic bias, and user bias[81,82].

Data bias occurs when the training data for machine learning models is unrepresentative or incomplete, leading to biased results. This can happen if the data comes from biased sources or lacks important information.

Algorithmic bias arises when the algorithms themselves have built-in biases, often due to biased assumptions or criteria used in decision-making.

User bias occurs when individuals using AI systems unintentionally introduce their own biases, either through biased training data or in their interactions with the system.

To address these biases, several strategies can be employed:

1.Dataset Augmentation: Adding diverse data to training sets to improve representation and reduce bias.

2. Bias-Aware Algorithms: Designing algorithms that take various biases into account and aim to minimize their influence.

3. User Feedback Mechanisms: Collecting user feedback to identify and correct biases within the system.

Ongoing research is focused on developing new methods to tackle bias in AI, emphasizing the need for equitable and fair AI systems for all users[83].

Fairness in AI is a complex concept that has sparked considerable debate in academic and industry circles. At its essence, fairness means ensuring that AI systems are free from bias and discrimination. (11) Characterizing different types of AI fairness definitions.(fig 4) [84].

Type of Fairness	Description	Examples
Group Fairness	Ensures that different groups are treated equally or proportionally in AI systems. Can be further subdivided into demographic parity, disparate mistreatment, or equal opportunity.	1. Demographic parity: Positive and negative outcomes distributed equally across demographic groups [31]. 2. Disparate mistreatment: Defined in terms of misclassification rates [30]. 3. Equal opportunity: True positive rate (sensitivity) and false positive rate (1-specificity) are equal across different demographic groups [11].
Individual Fairness	Ensures that similar individuals are treated similarly by AI systems, regardless of their group membership. Can be achieved through methods such as similarity-based or distance-based measures.	Using similarity-based or distance-based measures to ensure that individuals with similar characteristics or attributes are treated similarly by the AI system [25].
Counterfactual Fairness	Aims to ensure that AI systems are fair, even in hypothetical scenarios. Specifically, counterfactual fairness aims to ensure that an AI system would have made the same decision for an individual, regardless of their group membership, even if their attributes had been different.	Ensuring that an AI system would make the same decision for an individual, even if their attributes had been different [35].
Procedural Fairness	Involves ensuring that the process used to make decisions is fair and transparent.	Implementing a transparent decision-making process in AI systems.
Causal Fairness	Involves ensuring that the system does not perpetuate historical biases and inequalities.	Developing AI systems that avoid perpetuating historical biases and inequalities [4–6].

Fig. 4 Types of AI Fairness

Addressing equality challenges in surgical care requires multifaceted approaches. Collaboration among healthcare organizations, policymakers, and communities is essential to reduce gaps and promote equity.

Key strategies include:

Culturally Sensitive Care: Implementing practices that respect diverse cultural backgrounds.

Improved Health Insurance: Enhancing coverage to make surgical care more accessible.

Access Expansion: Increasing surgical services in underserved areas.

Diversity and Inclusion: Promoting a diverse workforce in surgical specialties.

Effects on patient

AI can also help advance equity by improving diagnostic accuracy, streamlining care pathways, and reducing variations in treatment outcomes. However, it's crucial that AI algorithms are developed and tested on diverse patient groups to avoid reinforcing biases.

Significant barriers remain, including socioeconomic, racial, ethnic, geographic, and gender disparities in access to surgical care and outcomes. By identifying and addressing these gaps, healthcare stakeholders can implement targeted interventions and regulations, using AI technology to enhance fairness in surgical treatment. Achieving equity requires a collaborative effort grounded in a thorough understanding of the root causes of disparities in surgical practices[85]

Patient flow management is a vital aspect of healthcare. It refers to the ability of healthcare systems to effectively manage patients as they progress through various stages of care, ensuring minimal delays while maintaining quality and patient satisfaction[86].Data-driven solutions in mental health offer a wide range of possibilities. AI can enhance our understanding of the causes of mental health conditions, improve detection and diagnosis, develop risk-based strategies, support decision-making, and help redesign services to better meet patients' needs.[87].

Trust

Trust is essential for the ongoing social acceptance of AI. The European Commission's AI High-Level Expert Group (AI HLEG) emphasizes that if AI systems fail to demonstrate trustworthiness, their widespread acceptance and adoption will be limited, preventing society from realizing the significant potential benefits, both social and economic**.** [88].

Building trust in AI involves several key factors:

1. Representation: The way AI is presented can impact trust. Humanoid robots, for example, are popular because their human-like features help people form emotional connections. Similarly, robot dogs, which symbolize loyalty and companionship, are often easier for people to trust.

2. Image/Perception: The portrayal of AI in sci-fi literature and films often paints a negative picture, suggesting that advanced AI could become a threat. This perception can significantly affect initial trust in AI systems.
3. User Reviews: Online reviews play a crucial role in shaping trust. Positive reviews can enhance initial trust, while negative feedback can undermine it.
4. Transparency and Explainability: Trust in AI requires understanding how systems are programmed and how they make decisions. If AI lacks transparency or fails to explain its actions, trust is likely to be diminished. The “black box” nature of some machine learning processes poses a challenge in this regard.
5. Trialability: Allowing potential users to experience AI applications before fully adopting them can foster trust. People are often resistant to new technologies, especially if they lack familiarity. Providing opportunities to try out AI can enhance understanding and build confidence.

By addressing these factors, developers and organizations can improve trust in AI systems, facilitating broader acceptance and use[89].

Effects on healthcare professionals

Artificial Intelligence (AI) is transforming healthcare by enhancing clinical procedures, improving patient outcomes, and optimizing resource allocation. Healthcare professionals can leverage AI algorithms to analyze large datasets, identify patterns, and make timely, informed decisions.Artificial intelligence (AI) has the potential to significantly transform healthcare in various ways. It is making substantial contributions in several key areas, including:

1.Medical Imaging: AI algorithms can analyze medical images, such as X-rays, MRIs, and CT scans, with remarkable accuracy. This capability helps radiologists quickly detect abnormalities and diseases in their early stages.

2.Diagnosis and Disease Prediction: AI models can evaluate patient data, including medical history, symptoms, and test results, to assist doctors in making more accurate diagnoses and predicting disease progression.

3.AI algorithms can evaluate large datasets to identify potential drug candidates, predict their efficacy, and streamline the drug development process. This helps reduce the time and costs associated with bringing new drugs to market.

4.Personalized Medicine: AI can leverage genomic data and other individual patient characteristics to tailor treatment strategies, optimizing effectiveness while minimizing adverse reactions.

5.Remote Monitoring and Telemedicine: AI-powered devices and algorithms enable remote monitoring of patients' health conditions, facilitating telemedicine consultations. This advancement improves access to healthcare services, especially in rural or underserved areas[90 ,91].

Data privacy and security

Data privacy and security have evolved significantly from the era of manual record-keeping. The digital age brought new challenges, as data became more accessible but also more vulnerable. This shift led to the development of technologies like encryption and firewalls to safeguard sensitive information.Artificial intelligence has further transformed data privacy and security by enabling the analysis of vast amounts of data to identify patterns and potential threats in real time. This capability helps protect data and prevent security breaches.

Benefits of Automation in Data Security

Efficiency: Automation significantly speeds up data protection processes, completing tasks in seconds that might take humans hours or even days. This rapid response is crucial for preventing or mitigating security issues.

Reliability: By minimizing human error, a major cause of data breaches, AI ensures that security measures are consistently applied and effective.

Scalability: Automated systems can easily adjust to fluctuations in data volume and business growth, making it simpler to manage large amounts of data and complex environments.

Insightful Analytics: Automation provides precise insights into data analysis, helping identify security threats or unusual activities that might otherwise be overlooked[92].

Fig. 10 Privacy and security concerns in generative AI in 5 perspectives.(fig5)

One of the main limitations of machine learning and deep learning approaches is their need for large datasets for development and testing—often much larger than what is typically collected in most prospective clinical trials. In contrast to other medical fields, such as obstetrics, ophthalmology has benefited from the availability of extensive, well-curated imaging datasets. As a result, it is often viewed as being at the forefront of AI-enabled healthcare[93].

Data privacy

Data privacy is crucial in healthcare, especially when developing machine learning (ML) systems. For instance, if a medical study uses electronic health records (EHR) data but the data owner and the computation team are different, the sensitive data must be sent securely. However, this data is often stored in its original form on the server, which leaves it vulnerable to attacks from both insiders and outsiders. This presents a significant risk.Privacy concerns include the specific features, membership, and values of the data. There are three main types of data privacy attacks:

1. Re-identification: Linking anonymized data back to individuals.

2. Reconstruction attacks: Rebuilding original data from available information.

3. Property inference attacks: Deducing sensitive attributes from the data [94].

Due to its private and sensitive nature, healthcare data, which includes a patient's medical history, diagnoses, treatment plans, and personal information, has a special place in the digital age. As the healthcare sector quickly adopts digital technology and data-driven solutions, protecting privacy has become a top priority. Protecting the privacy of healthcare data is more important than ever at a time when electronic health records (EHRs), telemedicine, wearable technology, and networked healthcare systems are the standard [95)]Advancements in healthcare have resulted in medical equipment generating vast amounts of digital data, commonly referred to as medical big data. This data is complex and challenging to analyze, but it contains valuable insights that could enhance healthcare, like predicting epidemics and improving treatment decisions. The abundance of this data makes healthcare an appealing area for a branch of AI known as machine learning.[95] Marketing scholarship has increasingly highlighted the importance of engaging customers on cognitive, emotional, and behavioral levels to build long-term relationships. This requires significant investment in understanding customers' preferences, feelings, and behaviors. As a result, many companies have implemented consumer data collection initiatives, utilizing tools from simple loyalty cards to advanced video monitoring and GPS tracking. This focus on deeply understanding customers has led to the widespread use of big data and analytics in marketing.[95]

Security :

Healthcare organizations handle vast amounts of data to ensure efficient and effective care. However, securing this data has been a significant challenge for many years. The healthcare sector is particularly vulnerable to data breaches, as attackers often use data mining techniques to uncover and publicly release sensitive information. Implementing security measures is complex, and as attack methods become more advanced, the risks increase. Therefore, it's essential for healthcare organizations to adopt robust data security solutions that not only protect critical information but also comply with industry regulations. [98]

Privacy and security concerns in big data

Privacy and security are critical issues in big data. Privacy refers to the ability to safeguard sensitive personal health information, emphasizing the governance of how individuals' data is collected, shared, and used through policies and authorization processes. On the other hand, security involves protecting data from unauthorized access, theft, and attacks, ensuring its integrity and availability. While security is essential for data protection, it is not enough to fully address privacy concerns. Both aspects must be effectively managed to protect individuals' sensitive information. [96]

Malicious Use of AI

Social Engineering - refers to attacks that rely on deception to trick individuals into sharing sensitive or personal information. Attackers manipulate people into providing this information, which can then be used for fraudulent activities. [97]

Intrusion Detection System (IDS) - An Intrusion Detection System (IDS) is a key security tool designed to detect, prevent, and respond to cyber attacks. It monitors activities such as network traffic and system audits to ensure security. The main goal of an IDS is to efficiently identify any intrusions.[98]

Malware Overview malware has been a threat for decades, starting with the Creeper Worm in the 1970s, which was the first known malicious software. Today, malware has evolved into a major cyber security issue.

Current Statistics:

The AV-TEST Institute reports over 350,000 new malware and potentially unwanted applications (PUAs) are registered daily about four every second. As malware creators become more innovative, developing complex and harder-to-detect programs, it poses challenges for defense mechanisms. There are also concerns about the potential use of artificial intelligence to create more effective malware, though this technology is still in its early stages.[99]

Digital Security and AI in Cyber attacks - The integration of artificial intelligence (AI) in cyber attacks can streamline and enhance the effectiveness of these attacks, reducing the tradeoff between their scale and efficiency. This could lead to a rise in labor-intensive attacks, like spear phishing, which target individuals more precisely.

Potential Threats:

Human Exploitation: AI could be used to create realistic impersonations using speech synthesis, making it easier to deceive people.

Software Vulnerabilities: Automated hacking tools could exploit existing weaknesses in software systems.

AI Vulnerabilities : As AI systems become more common, they may also present new targets for attacks. Overall, AI could significantly expand the landscape of cyber threats by introducing novel attack methods.[100]

Cyber security and QR Code Vulnerabilities - Hackers often use various methods to create misleading links, aiming to control victims' devices or access sensitive information online. QR codes, which are two-dimensional barcodes readable by smartphones, can also be manipulated due to the lack of standardized generation protocols. This vulnerability exposes them to various attacks.[101]

Efforts to limit access to certain research to reduce potential harm face several significant challenges:

Composition Problem: Innocent pieces of research can be combined in harmful ways, leading to malicious applications.

Slow Drip Problem: Research advancements often happen gradually, making it hard to distinguish between safe and dangerous research.

Conflation Problem: Many research fields, such as natural language processing and computational photography, can lead to developments that may be weaponized, like creating convincing dialogue that can manipulate people.

Defector Problem: Even if researchers agree not to pursue specific areas of research, individuals or organizations may ignore these agreements, gaining a competitive edge by exploiting the knowledge.

These challenges complicate efforts to control the release of research and highlight the need for careful evaluation of release practices. Despite these difficulties, implementing effective release strategies could help slow the deployment of harmful technologies and mitigate potential risks[100]

Future of AI in Healthcare

Artificial Intelligence (AI) is transforming healthcare by improving patient care, diagnosis, and treatment methods. The documentary “Decoding the Future: Artificial Intelligence in Healthcare” explores AI’s significant impact and the challenges it poses in this evolving field. AI technologies are pushing healthcare towards a major change, and this article serves as a guide to navigate the complex possibilities AI offers for better health outcomes.(16)

AI has great potential in healthcare, particularly in nursing, by enhancing care quality and efficiency and enabling personalized medicine. As more health data becomes available, AI can reduce care variability, improve precision, speed up discoveries, and address disparities. It can empower patients and support healthcare professionals with advanced research and analytics. However, there are challenges in understanding how to best use AI, including technological, systemic, regulatory, and attitudinal barriers. This paper explores the basics of AI, its applications in healthcare and nursing, and the key challenges to its successful implementation.(17)

The Future of Medicine: Artificial intelligence (AI) is transforming healthcare in several key ways. It enhances diagnostic accuracy through precision diagnosis, allowing for earlier detection and personalized treatment plans by analyzing large amounts of patient data. AI also enables proactive disease prevention by using predictive analytics to identify individuals at risk, facilitating early intervention. Additionally, AI is improving treatment methods and streamlining healthcare workflows, while raising important ethical considerations and future implications for the industry.(18

Medical interventions—visual art meets medical technology

Artists have long explored the connection between art and science, particularly in their representations of the human body. In the late 19th and early 20th centuries, this relationship evolved as artists moved away from traditional figurative depictions to portray the body in states of disintegration, decay, and deformity, reflecting deeper complexities and challenges.(19)

Preparing for the Future of Artificial Intelligence

In October 2016, the USA’s National Science and Technology Council released a report on Artificial Intelligence (AI). It outlined expected developments in AI, its potential impacts, and recommended actions for the government. The report was based on various sources and expert consultations, including five workshops. Additionally, a companion document titled “The National Artificial Intelligence Research and Development Strategic Plan” details a strategy for federally-funded AI research and development.(20)

Future of AI in Different Fields of Life

Artificial intelligence is the study of ideas to bring into being machines that respond to stimulation consistent with traditional responses from humans, given the human capacity for contemplation, judgment and intention. Each such machine should engage in critical appraisal and selection of differing opinions within itself. Produced by human skill and labor, these machines should conduct themselves in agreement with life, spirit and sensitivity, though in reality, they are imitations.(21)

Current Medicine Research and Practice

AI assists healthcare teams by digitizing patient data, which helps reduce documentation time and creates a database for diagnosis and treatment. Medical specialists work with tech professionals to develop tailored platforms for data collection and routine tasks. Custom software is created for specific applications, leading to the development of diagnosis, treatment, and post-treatment care modules that meet individual patient needs. Analyzing the collected data is crucial for the AI system's effectiveness.(22)

Human Resource Management Review

Many firms across various industries face a growing threat from data breaches, which can severely impact their corporate reputation. These breaches can lead to negative customer perceptions and, in the era of Industry 4.0, can be amplified by social media. This paper investigates how data breaches affect different dimensions of corporate reputation. It analyzes user-generated content on social media for 35 companies in nine industries that experienced breaches between 2013 and 2016. The breaches are categorized into three types: “intentional and internal,” “unintentional and internal,” and “intentional and external.” The study aims to assess changes in reputational dimensions following these incidents and to identify differences among the breach types.(23)

Iot and Ai in healthcare

The healthcare industry is significantly benefiting from IoT and AI technologies, especially as it faces pressure to reduce costs while managing a growing unhealthy population. These technologies enable greater interconnectivity within the healthcare ecosystem, offering substantial advantages for patients, doctors, insurers, and drug developers. IoT devices like smart pills, wearable monitors, and sensors allow continuous data collection, while

AI systems analyze this data to identify changes in patient conditions, suggest treatment options, and recognize trends. This integration supports patient adherence, enhances outcomes, and accelerates the discovery and accessibility of new treatments.(24)

Rise of Robotics And AI

Robotics and AI have advanced quickly, significantly impacting human life. However, these technologies have outpaced existing organizational, ethical, and regulatory systems. We are at a crucial moment where new business models and frameworks are needed to support these rapidly evolving technologies. This chapter outlines the development of these technologies and advocates for a proactive approach to the business and ethical challenges they present. (25)

Conclusion

Artificial intelligence is set to transform healthcare, offering significant advancements in drug discovery, patient care, clinical trials, and surgical interventions. Its ability to enhance precision, streamline processes, and support healthcare professionals holds great promise for improving patient outcomes and driving innovation in medicine. However, with these advancements come challenges such as data bias, privacy concerns, and ethical issues that must be addressed to ensure equitable and transparent healthcare solutions. To fully harness the potential of AI, it is vital to establish clear ethical frameworks, promote accountability, and ensure collaboration across sectors. By tackling these challenges, AI can usher in a new era of personalized, efficient, and accessible healthcare. The future of AI in healthcare is promising, but it will require responsible stewardship to ensure it benefits patients and society as a whole, transforming the healthcare industry for the better.

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