Transforming Medical Service Delivery with Artificial Intelligence: A Comprehensive Review of Current Applications

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Abstract. During the COVID-19 pandemic, public health and healthcare systems and institutions providing basic community services providing basic community services have been subjected to extraordinary and sustained demand. The allocation of many medical resources is often constrained by the availability of human resources and the impact of healthcare service processes. The explosive growth of AI has enabled it to alleviate some of the pressure on human resources in healthcare services to a certain extent. It has even advanced the transformation of healthcare service processes. Based on the categorization of healthcare services, this review aims to examine the impact of AI on various stages of healthcare services, improving the efficiency of healthcare services, and providing potential research directions for relevant researchers.

Keywords: Artificial Intelligence, Healthcare Service Process, Disease Diagnosis, Personalized Medicine, Robotic Surgery.

1. Introduction

At the Dartmouth Conference in 1956, the concept of "artificial intelligence" was first proposed, establishing the goal of "using machines to simulate human intelligence" [1]. During this period, the worldview of "intelligence is a program" emerged, giving rise to technologies like expert systems and decision trees [2], which are highly explainable and transparent in their reasoning. However, they rely on manual knowledge and lack learning capabilities. In 1943, the first mathematical model of a neuron was invented, laying the mathematical foundation for neural networks [3]. By mimicking the brain's neural networks and adjusting the weights of unit connections to achieve learning, but limited by computing power and data, it has only begun to develop rapidly in the last decade. Today, AI has already come very close to human performance in certain aspects, even significantly surpassing it [4].

In recent years, the allocation of medical resources has often attracted significant societal attention, especially during the COVID-19 pandemic. Research indicates that the distribution of medical resources is usually constrained by the availability of human resources and the impact of healthcare service processes [5]. The efficiency of healthcare services often plays a decisive role during the pandemic. Based on the classification of healthcare service processes, this paper reviews the impact of AI on healthcare services, aiming to improve the efficiency of healthcare services and provide potential research directions for relevant researchers.

2. AI Aids in Developing Medical Plans

2.1 Triage and Pre-consultation

Patients often encounter various issues before seeking medical consultation, such as registration, waiting, payment, etc. Meanwhile, due to a lack of basic medical knowledge and negative emotions caused by the discomfort of the illness, there is often blind questioning, which reduces the efficiency of medical services. However, in recent years, with the improvement of natural language processing (NLP) capabilities, AI can communicate with patients based on specific medical knowledge and the patients' emotions [6].

West China Hospital of Sichuan University has achieved 100% accuracy in emergency triage (MEWS score) using an optimized GPT-4 model, with an overall accuracy rate of 92.63% in outpatient departments, including specialties like ophthalmology, which reached 100% [7]. In a study published in *Nature*, professional physicians evaluated Google Health's AMIE system. It showed higher accuracy and better performance in 30 of 32 indicators, with empathy skills receiving higher patient praise [8]. However, currently, natural language processing (NLP) in the medical field is still limited by experimental data or sample size, and most studies have not significantly provided information about the potential impact of this technology on medical care or patient outcomes, which restricts the credibility of its conclusions [9].

2.2 Disease Diagnosis

Medical errors are a significant cause of death. Among them, the percentage of diagnostic errors, including misdiagnosis, missed diagnosis, and delayed diagnosis, accounts for 10–26% of all cases [10-11]. Meanwhile, due to increased workload, fatigue has become one of the primary non-professional reasons affecting the accuracy of doctors' reporting in the workflow [12]. On this basis, AI's evident lack of fatigue and high efficiency can significantly reduce the burden on doctors.

Adopting improved CycleGAN and ResNet models to predict FD PET images. Amirhossein Sanaat reduced the detection time for clinical WB 18F-Fluorodeoxyglucose (18F-FDG) PET/CT to just one-eighth of the original time. This allows for a moderate reduction in injection and shortening of acquisition time during PET scans, maximizing the reduction of potential radiation hazards and improving patient comfort [13]. Zhi Li proposed a label-free optical biopsy technique, integrating three imaging modalities: SRS (stimulated Raman scattering), SHG (second harmonic generation), and TPF (two-photon fluorescence). Combined with deep learning, it enables early diagnosis of diabetic nephropathy, avoiding tissue damage from traditional biopsies, achieving 3D imaging and lipidomics analysis, and identifying early collagen morphological changes and oxidative stress markers [14].

AI can stably handle repetitive diagnostics tasks 24 hours a day, significantly compressing diagnostic process time, allowing the same equipment to serve more patients, and alleviating the pressure of shortages in high-end equipment. At the same time, AI is also promoting non-invasive/minimally invasive diagnostic alternatives, reducing the risks of medical diagnostics. In some tests, it has also improved patient comfort. High-intensity repetitive tasks free doctors from mechanical image interpretation, allowing them to focus on complex decision-making and patient communication. These technologies not only validate the core value of AI in reducing medical error rates (addressing fatigue and efficiency pain points) but also bridge the gap between human physiological limitations and the demand for diagnostic accuracy through technological means. The trend of "reducing invasive procedures" presented in the cases reshapes patient-centered diagnostic ethics.

2.3 Medication Recommendations

The application of artificial intelligence in drug recommendation is evolving from an auxiliary tool to a core decision-support system for personalized treatment. This technology constructs predictive models by integrating multimodal data (including genomics, clinical records, pharmacokinetics, and real-world efficacy data) to achieve the "four pillars of precision medication": administering the right drug to the right patient at the right time with the correct dose [15].

The current mainstream methods primarily follow two technical approaches: fusion of deep learning and knowledge graphs, and multimodal data collaborative modeling. The complex relationships between drugs, targets, and diseases are modeled using graph neural networks (GNNs) and the Transformer architecture to process temporal data such as electronic health records. For example, the iPharma system optimizes dose for narrow therapeutic index drugs like vancomycin, with a clinical application dose recommendation accuracy of over 85% [15].

Integrating drug molecular structures (SMILES sequences), protein binding site predictions (such as the EquiPocket model), and patient gene expression features, breaking the limitations of traditional pharmacokinetic models that rely on only a few clinical parameters [16]. Yue Lin et al. demonstrated through ablation experiments the necessity of each component in AMHSC, while adaptively determining the number of reads MemNN performs based on the patient's specific situation to obtain optimal reasoning information from MemNN, thereby refining the patient's health status representation vector and enhancing drug recommendation performance [17].

AI is driving drug recommendations from a "one-size-fits-all" approach to a "personalized medicine" approach while ensuring fairness in healthcare resources. For example, grassroots doctors can obtain expert-level medication guidance through AI tools, narrowing the urban-rural healthcare gap. However, model effectiveness is currently limited by the completeness of labeled data, and fragmented grassroots healthcare data can lead to recommendation biases. Deep learning models lack interpretability, making it difficult for doctors to understand the logic behind AI recommendations. However, what needs to be emphasized is that the application of AI in healthcare remains based on the physician-centric model. The intelligent drug recommendation function merely recommends disease treatment plans to clinical doctors for decision-making, rather than replacing them in making decisions.

3. Execution of Auxiliary Medical Programs

3.1 Surgery

Similar to the impact of AI on vehicles, drawing from the field of autonomous driving, the six-level autonomy grading system proposed by Yang et al. (further elaborated by Lee et al.) is adopted, ranging from no autonomy to full autonomy [18]. At the lowest level, the robot is entirely controlled by a doctor and has no autonomous capabilities. Representative systems include the Da Vinci surgical system (Intuitive Surgical Inc.) and domestic systems such as the Edge MP1000, Toumai MT1000, and KangDuo SR1000 [19]. These systems may have control algorithms (such as hand tremor filtering), but the operational control remains entirely in the hands of the doctor. At the highest level, level 5, the robot becomes a "robotic surgeon," capable of independently completing the entire surgery. This is still in the research phase, facing significant technical challenges, and has no commercial applications [20].

In this concept, the closest level is autonomy level 4, where high-level autonomous robots can generate and select the optimal surgical plan, with the doctor merely supervising. The key is multimodal data learning (such as the Brainlab iPlan system autonomously segmenting brain tissue MRI [21]). However, soft tissue segmentation technology is still in the research phase (such as the Marahrens team locating tumors in pig livers, and the Ge team marking tongue tumors with an error level close to that of doctors [22]). This level reduces the burden on doctors while retaining supervisory authority.

Currently, AI is similar to the brain of a surgical robot, giving it greater autonomy. However, surgical robots still struggle to handle special situations like autonomous driving. Robots find it challenging to process dynamic changes in real time, such as the deformation of soft tissues or bleeding obscuring vision (e.g., intestinal peristalsis, intraoperative bleeding), leading to increased positioning errors. Although optical imaging (e.g., light field cameras) is used for brain tissue segmentation (Brainlab iPlan), the real-time recognition accuracy for soft tissues (e.g., liver, intestines) remains insufficient, requiring manual corrections. Most systems lack realistic force feedback, potentially causing damage to fragile tissues (e.g., nerves, blood vessels) [18-22].

Additionally, the purchase price of a single device (e.g., the Da Vinci system) exceeds one million dollars, with high maintenance and upgrade costs. Most surgeries are not covered by insurance, further burdening patients. Operators must relearn human-robot collaboration logic, and senior doctors generally resist AI-driven decisions.

3.2 Medical Support Behavior

The deep integration of artificial intelligence (AI) technology is reshaping the field of medical robotics in unprecedented ways, particularly driving significant advancements in its intelligence level for non-contact, unmanned operation scenarios. This enhancement is primarily driven by three core capabilities: environmental perception, decision-making optimization, and autonomous collaboration, forming the technical pillars of next-generation intelligent medical robots [23]. By integrating these technologies, medical robots can execute preset programs and dynamically understand, analyze, and respond to complex and ever-changing real medical environments, significantly improving their operational autonomy, safety, and efficiency.

In the critical application of environmental disinfection, AI-powered disinfection robots represent the technological forefront of this field. The core of these robots is an intelligent system built on advanced artificial intelligence algorithms. This system is far more than just automating fixed routes; it endows the robots with the ability to interact intelligently and in real-time with the disinfection environment [24]. The realization of this interaction relies on powerful machine vision technology, particularly object detection algorithms based on deep learning (such as YOLO, SSD, Faster R-CNN, etc.). Equipped with high-resolution cameras and depth sensors, the robots can accurately identify various surfaces, objects, and even specific areas requiring disinfection (such as high-frequency contact points), and precisely distinguish between disinfection zones, passable areas, and obstacles. After target identification, the built-in AI decision engine autonomously plans the optimal disinfection path based on the real-time map of the environment and the target location information. This considers the shortest distance or time and comprehensively evaluates disinfection coverage's uniformity, thoroughness, and operational efficiency. More importantly, while performing disinfection operations (such as spraying disinfectants or using ultraviolet light), the robots can leverage multi-sensor fusion technology (such as LiDAR, ultrasonic sensors, depth cameras, IMUs, etc.) to perceive environmental changes (such as moving objects or temporary obstacles) at millisecond-level precision and achieve high-precision, high-reliability dynamic obstacle avoidance, ensuring a safe, collision-free operation process [24]. This level of intelligence significantly reduces the need for manual intervention, lowering the risk of workers’ exposure to disinfectants or pathogens, and enhancing the standardization and traceability of disinfection operations.

For highly infectious diseases (such as certain respiratory infections, severe contagious illnesses, etc.), ensuring the timely and accurate delivery of critical supplies like medications and samples without endangering the safety of healthcare workers and patients has become an urgent challenge. Against this backdrop, AI-driven medication/material delivery robots demonstrate significant potential. As the method adopted by researchers like Srikanth Kavirayani, these robots utilize AI technology to achieve reliable transportation in complex environments [25]. The core technology lies in constructing a robust autonomous navigation and decision-making system. By integrating Simultaneous Localization and Mapping (SLAM) technology, precise path planning algorithms, and real-time obstacle detection and prediction modules, delivery robots can not only navigate through structured hospital corridors but also safely operate in relatively crowded or dynamically changing areas (such as emergency rooms, the periphery of isolation zones). The core objective of the system is to ensure that, at any given time, the robot's movement path is completely collision-free with other mobile robots, healthcare workers, patients, visitors, and even mobile equipment (such as beds or carts), achieving an accurate "zero-contact" delivery [25]. The AI system also possesses task recognition and priority management capabilities to enable timely delivery. This is typically achieved by setting indicators in the robot task scheduling or backend management systems. These indicators may be based on electronic prescription information integration from hospital information systems, on-site recognition using specific tag cards or signals, or triggered by healthcare workers via portable terminals for urgent task requests.

4. Rehabilitation Assistive Devices

4.1 Function Compensation

With the development of AI, multimodal signal processing has advanced. Particularly in prosthetics, people have begun to explore using various types of information for prosthetic control. The Jianwei Cui team, based on visual fusion information from miniature LiDAR and pinhole cameras, detects the scale information of grasped objects to control the grasping posture of the robotic hand automatically; based on arm movement and toe tactile information, it controls the flow of grasping movements, achieving a success rate of 91.63% [26].

4.2 Rehabilitation Therapy

Leveraging AI's ability to learn from data and make precise predictions, insoles can extract gait features. These insoles can identify whether the wearer is sitting, standing, walking, or lying down. They can also distinguish between normal gait and Parkinson's disease gait characteristics, which are essential in measuring the improvement in exercise outcomes after training [27].

5. Conclusion

Artificial intelligence has deeply penetrated and reshaped the core aspects of healthcare service processes, demonstrating significant potential and notable outcomes in enhancing service efficiency (such as reducing waiting and examination times), improving diagnostic accuracy (such as enhancing triage, diagnosis, and medication precision), optimizing resource allocation (such as automating support tasks), enhancing patient experience (such as non-invasive diagnostics and empathetic interactions), and pioneering new treatment methods (such as advanced robotic surgery and intelligent rehabilitation).

Despite AI's immense value in healthcare service processes, this research also reflects some current limitations and challenges in its application. Many AI applications (especially those based on deep learning for NLP and image analysis) heavily rely on high-quality, large-scale labeled datasets. Medical data faces fragmentation, strict privacy protection, high labeling costs, and sample bias, which limit the model's generalization ability and clinical applicability. The study also points out that many current AI research efforts have not fully evaluated their long-term impact on clinical outcomes and care quality. Complex deep learning models are often seen as "black boxes," with their decision-making processes difficult to interpret. This reduces trust from doctors and patients in AI results in critical scenarios such as medical diagnosis and treatment recommendations, hindering clinical adoption. Highly interpretable AI (such as early expert systems) has limited capabilities, while powerful AI lacks interpretability.

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