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The Impact of Digital Health Technologies and Artificial Intelligence on the Enhancement of Preventive Healthcare Systems: A Comprehensive Review

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Abstract

Background: The escalating costs of healthcare, exacerbated by the COVID-19 pandemic, have underscored the urgent need for innovative solutions within global health systems. The rise in chronic illnesses and an aging population necessitate enhanced preventive healthcare strategies that leverage technology.

Methods: This review synthesizes existing literature on the role of digital health technologies (DHTs) and artificial intelligence (AI) in preventive healthcare. It examines various modalities, including mobile health, telemedicine, and wearable devices, and their impact on disease management, patient engagement, and healthcare accessibility.

Results: Findings reveal that DHTs significantly improve preventive healthcare by enabling early detection and monitoring of chronic conditions. AI facilitates enhanced decision-making through advanced imaging techniques and predictive analytics, which can lead to more accurate diagnoses and personalized treatment plans. However, challenges such as data privacy concerns, the digital divide, and the need for robust regulatory frameworks remain critical issues to address.

Conclusion: The integration of technology in preventive healthcare offers promising avenues for improving patient outcomes and system efficiency. Nevertheless, addressing ethical considerations and ensuring equitable access to these technologies is essential for maximizing their benefits. Future research should focus on developing comprehensive strategies to overcome existing barriers, ensuring that technological advancements align with patient-centered care principles.

Keywords: Preventive healthcare, digital health technologies, artificial intelligence, chronic disease management, healthcare accessibility.

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1. Introduction

Global health systems are at a pivotal juncture, with rapidly escalating healthcare costs that have significantly exceeded GDP growth rates, jeopardizing the viability of health systems [1]. This issue became rather clear with the onset of the 2019 coronavirus disease (COVID-19) epidemic and the conflict in Ukraine. A confluence of constrained finances, an aging population, increasing chronic illnesses, and the pressure on healthcare institutions that have historically failed to meet heightened demands for service accessibility and availability exists. Furthermore, the COVID-19 pandemic is causing health system failures in several nations, such as India, Brazil, and Indonesia [2].

Health systems rely on robust disease management protocols and evidence-based care strategies to address needs and standardize practices by industrial healthcare delivery services. The notion of a Highly Reliable Organization (HRO) underscores the management of its services by either an Accountable Care Organization (ACO) or a Health Maintenance Organization (HMO) [3]. The prevalence of chronic illnesses in the United States is progressively rising, with 60% of persons affected by one chronic condition and 40% by more than two, resulting in yearly healthcare expenditures of USD 3.3 trillion [4]. Furthermore, this situation rapidly evolved with the emergence of an infectious illness, first reported in Wuhan, China, in 2019, and subsequently classified as COVID-19 by the World Health Organization on 11 February 2020 [5]. Since then, healthcare has been experiencing a digital transition that will alter many of the essential components of medical treatment [6]. This disease may result from the immense strain imposed by COVID-19 on global healthcare systems, infrastructure, supply chains, and personnel.

The epidemic compelled healthcare stakeholders to embrace digital technology [7,8]. Significant basic changes occurred in the healthcare industry after the epidemic. Contemporary patients exhibit active participation in healthcare-related decision-making, attributed to the heightened acceptability of virtual healthcare systems and related digital technologies [9]. Nevertheless, significant obstacles may arise, and the solutions to address them will facilitate the transition to the next healthcare era. Patient experiences and requirements drive developments in the healthcare industry. Their primary focus is the establishment of digitally enhanced physician–patient interactions and ensuring the availability of patient-centric services worldwide [10]. The deployment of modern digital devices is essential for enhancing customer happiness, enabling tracking, monitoring health state, and improving medication adherence [11]. These characteristics would be more advantageous during the post-hospitalization phase using digital health platforms. Simultaneously, healthcare consumers are apprehensive about disclosing their sensitive information; thus, healthcare organizations (HCOs) must maintain customer confidence by demonstrating openness, empathy, and dependability in their services [11-14].

The emergence of biomedical science, encompassing genomics, digital medicine, artificial intelligence (AI), and its subset machine learning (ML), underpins the transformation of healthcare, necessitating a new labor force and standards of practice. Genomics and other technologies, like as biometrics, tissue engineering, and the vaccine sector, have the potential to enhance and revolutionize diagnostics, medicines, care delivery, regenerative treatments, and precision medicine frameworks [15-22].

2. Digital health technologies (DHTs)

Digital health technologies (DHTs) encompass mobile health (mHealth), health information technology (HIT), wearable devices, telehealth, telemedicine, mobile Internet devices (MIDs), and personalized medicine [23-28]. Recently, advancements in artificial intelligence (AI), the metaverse, and data sciences are impacting smart health [30-34]. These technologies provide improved prevention, early identification of life-threatening disorders, and remote treatment of chronic conditions outside traditional care settings, such as via wireless observed therapy (WOT), using an innovative approach to monitoring therapy adherence [35-39]. The most promising approach is to provide and supply health services universally and at any time in the era of disruptive and minimally invasive medicine. MIDs enable the receiver to access essential resources, including related apps and social media. The uses of MIDs are extensive and allow professionals access to scientific databases such as Medscape, Web of Science, and Scopus. Social media networks, including YouTube, Facebook, WhatsApp, Wikipedia, and other instant messaging software, are accessible to both professionals and non-professionals. Digital health modalities using AI in healthcare are rapidly advancing in the post-COVID-19 period [40].

Artificial Intelligence, Machine Learning, and Digital Health Technologies have catalyzed a transformation in healthcare, particularly after the disruption of the global healthcare system by COVID-19. AI is now incorporating emerging technologies, such as the Internet of Things (IoT), with the decentralized health technologies (DHTs) used by customers. With the extensive integration of AI and ML in healthcare systems, the IoT is anticipated to evolve into the intelligence of things; the use of acquired data is poised to modify processes, hence influencing behavior and values [41]. Furthermore, intelligent medical technology, namely AI-driven solutions, has garnered much interest among the general populace,

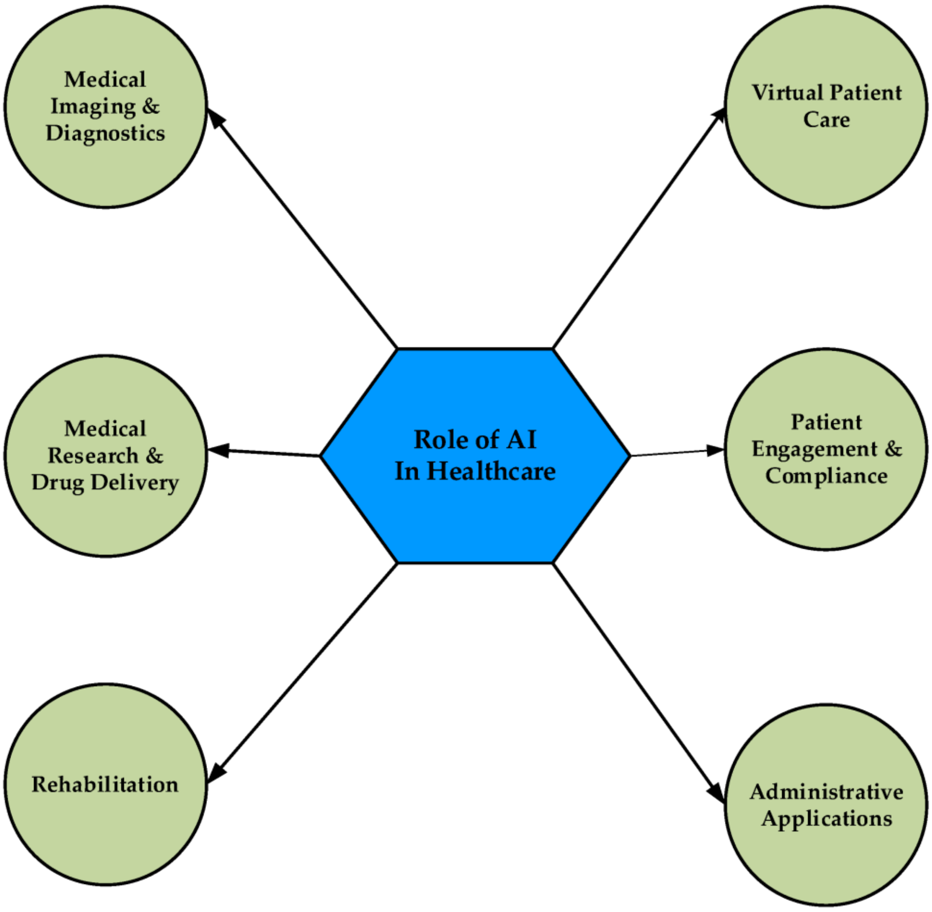

Figure 1. Utilization of artificial intelligence in several facets of healthcare.

as it facilitates the implementation of the 4P model of medicine—predictive, preventative, personalized, and participatory—thereby enhancing patient autonomy. The integration of AI into healthcare has shown improvements in efficiency, speed, and cost-effectiveness [42].

Digital health technologies provide healthcare practitioners with a comprehensive perspective of patient health by enabling access to patient data. They also enable doctors to provide patients with additional facts on their health. These provide genuine prospects to enhance treatment outcomes and effectiveness; yet there are apprehensions that such modalities may have a more significant psychological influence, especially with the prevalent use of SM and IMAs by patients, the public, and professionals [43]. Furthermore, aggregated data from various sources, including health information systems (HISs), wearable devices, telemedicine, mHealth, telehealth, medical imaging devices (MIDs), and other AI-driven medical technologies, generate substantial datasets that enhance the application of machine learning (ML) and artificial intelligence (AI) in healthcare systems. This is achieved through the learning processes derived from the data collected from these sources, encompassing research information, user experiences, and the analysis of extensive datasets [44,45]. Moreover, electronic health records (EHRs) include diverse healthcare information about individuals. Health information may be integrated utilizing innovative AI technology to provide precise insights into patient treatment.

AI has emerged as a viable option for large data applications in healthcare [46]. Furthermore, big data analytics empowers healthcare practitioners to enhance their clinical services by refining electronic health records using analytical algorithms [47]. These analytics use advancements in AI to filter extensive data on several criteria for enhanced data analysis [48]. This review seeks to elucidate the role of AI in healthcare, emphasizing the following key aspects: medical imaging and diagnostics, virtual patient care, medical research, and drug discovery, patient engagement and compliance, rehabilitation, and additional administrative applications. Furthermore, the authors discuss several problems associated with the use of AI in healthcare. These findings enhance the current research, advancing the advantages of AI technologies in healthcare (Figure 1).

3. Medical Imaging and Diagnostic Services

Artificial intelligence is an influential instrument for image processing, increasingly used by radiology experts for the early detection of various illnesses and for minimizing diagnostic inaccuracies in preventive contexts. Similarly, AI serves as an intelligent and promising instrument for the analysis of ECG and echocardiography data used by cardiologists to enhance their decision-making processes. The Ultromics technology, established at an Oxford hospital, employs AI to analyze echocardiogram images that detect heartbeat patterns and identify ischemic heart disease [49]. Artificial intelligence has shown promising outcomes in the early identification of ailments like breast and skin cancer, ocular illnesses, and pneumonia using body imaging techniques [50-52]. AI techniques examine speech patterns to predict psychotic events and identify characteristics of neurological disorders, including Parkinson's disease [53,54]. New research forecasted the development of diabetes via machine learning algorithms. The findings indicated that a two-class augmented decision tree was the most effective model for predicting several diabetic factors [55].

Moreover, Gudigar et al. [56] said that various medical imaging modalities, such as X-ray, computed tomography (CT), and ultrasound (US), using AI methodologies have substantially facilitated the fight against COVID-19 by enhancing early diagnosis. Their findings indicated that handmade feature learning (HCFL), deep neural networks (DNN), and hybrid techniques successfully predicted COVID-19 instances. A recent study provided a comprehensive explanation of the use of CT scans, X-rays, MRIs, and ultrasounds in the diagnosis of COVID-19. It indicated that AI has been crucial in assisting the public in combating the formidable pathogen [57]. Additionally, a deep learning model known as a transformer is used in medical imaging analysis, including registration, detection, classification, image-to-image translation, segmentation, and video-based applications [34]. Prior research elucidated the use of transformers in distinguishing COVID-19 from pneumonia by X-ray and CT imaging to fulfill the critical need for the rapid and effective management of COVID-19 patients [58,59]. A further research used the ImageNet-pretrained vision transformer (ViT)-B/32 network to identify COVID-19 using inputs including patches of chest X-ray images [60].

Wang et al. [61] suggested a novel hybrid technique using chest CT for the automated detection of COVID-19. This is a computer vision diagnostic method using wavelet Renyi entropy (WRE) and an innovative three-segment biogeography-grounded optimization (3SBBO) algorithm. It consists of WRE, a feedforward neural network (FNN), and the 3SBBO algorithm. WRE retrieves image features; 3SBBO improves the network's biases and weights; and the FNN classifies the pictures. This technique demonstrated superior performance compared to the kernel-based extreme learning machine, the extreme learning machine using the bat algorithm, and the radial basis function neural network in the detection of COVID-19. Furthermore, Gheflati et al. [62] indicated that the ViT is used to classify normal, malignant, and benign breast tissues using ultrasound (US) pictures. It demonstrated superior performance in the categorization of US breast pictures compared to convolutional neural networks (CNNs).

Moreover, AI encompasses the utilization of artificial neural networks, specifically deep learning methodologies known as Generative Adversarial Networks (GANs), which influence the domain of radiology. GANs include two artificial neural networks: (i) a generator that produces pictures resembling actual images, and (ii) a discriminator that identifies the distinction between synthetic and genuine images. In the realm of radiology, the generative model is capable of reproducing pictures in accordance with the training data and generating novel images that embody the characteristics of the training dataset. The discriminant model is trained to categorize pictures, such as determining the presence or absence of pneumonia on a radiograph. The conclusion was that the generator model, when trained with the discriminator model, may enhance radiological tasks such as anomaly detection, image synthesis, and cross-domain image synthesis [63]. Proficient radiologists struggled to differentiate between lung cancer nodule pictures produced by GANs and authentic ones [64]. Furthermore, GANs provide a significant possibility to enhance medical teaching and research. They rapidly create instructional materials and simulations for student education. For example, when students struggle to distinguish between “lower lobe collapse” and “consolidation,” examples of each kind might be created and shown to them. Consequently, synthetic data may enhance student learning by providing resources for edge-case scenarios. Moreover, synthetic control arms have been created by modeling placebo groups based on historical data, which reduces the need for an actual placebo group, hence lowering expenses and increasing the number of treatment arms in clinical trials [65].

Moreover, ChatGPT is a deep learning-based big language model used by the public for medical guidance, thereby raising significant concerns. The public may be inclined to use such a model to ascertain potential diagnoses based on clinical characteristics or to get treatment recommendations, therefore substituting expert medical counsel [66]. A prior survey conducted in the United States revealed that around one-third of individuals sought Internet-based medical guidance for self-diagnosis. Subsequently, almost fifty percent of them sought medical consultation over the Internet-based results [67].

In addition, AI-driven medical practice, particularly in medical imaging-guided diagnosis and treatment, is supported by a metaverse of "medical technology and AI" (MeTAI). The essential uses of MeTAI include "virtual comparative scanning," "raw data sharing," "augmented regulatory science," and "metaversed medical intervention." The MeTAI ecosystem's model execution is delineated as follows: The patient's scans are first simulated by virtual machines to determine the optimal imaging result prior to the real CT scan. A genuine scan is conducted based on this information. Thereafter, the metaverse pictures are disseminated to the patient's medical team with the patient's consent. In accordance with security protocols, the tomographic raw data and pictures are sent to the medical researchers. The aggregation of authentic and simulated visuals, data, and more medical evidence may be integrated into the metaverse and used in enhanced clinical trials. Finally, the patient has a metaverse-assisted remote robotic procedure and is thereafter monitored in the metaverse for rehabilitation if deemed therapeutically necessary. MeTAI encounters issues including security, inequality, investment, and privacy [68].

Moreover, medical scans are methodically collected and stored for a duration and are readily accessible for the training of AI systems [69]. These AI systems may decrease the time and expense associated with analyzing medical scans, perhaps enabling a greater number of scans for better-targeted management [70]. Artificial intelligence influences clinical decision-making and illness diagnosis. It can process, analyze, and present extensive data across many modalities for illness diagnosis and clinical decision-making. It may assist clinicians in making improved clinical judgments or perhaps replace human judgment in therapeutic areas [71]. Moreover, studies using computer-aided diagnostics have shown exceptional sensitivity, accuracy, and specificity in detecting subtle radiographic anomalies, with the potential to enhance public health. However, outcome evaluation in AI imaging research is often characterized by lesion identification, overlooking the biological severity and nature/type of a lesion, potentially resulting in a distorted representation of AI performance. Furthermore, the use of non-patient-related radiological and pathological endpoints may enhance predicted sensitivity, but at the expense of elevating false positives and perhaps leading to overdiagnosis by identifying modest anomalies that might resemble subclinical illness [72].

4. Telehealth Services

Baig et al. [73] observed that the progression of wearable technology and the prospects of using machine learning and artificial intelligence in healthcare is a concept that has been previously investigated. Consequently, patient monitoring and management via virtual care using effective and intelligent wearable technology solutions have become a reality and an integral component of standard care. Furthermore, AI contributes to the management of chronic conditions like diabetes mellitus, hypertension, sleep apnea, and chronic bronchial asthma via the use of wearable, non-invasive sensors. [74]. Prior research advocated for an intelligent sensor system using an integrated sensor network to monitor an individual's residence and surroundings, therefore acquiring data on the person's health condition and behavior. The suggested platform comprises inconspicuous, biomedical, and wearable sensors. These sensors track physiological parameters like respiration rate, pulse rate, breathing waveform, blood pressure, and electrocardiogram (ECG). A smart device, such as a tablet, has been suggested to serve as an interface between the individual and the sensors. The gathered data is sent to the cloud for storage and analysis pertaining to geriatric care [75]. A case study by Patel and Tarakji [76] examined a woman in whom atrial fibrillation was identified as the likely cause of her stroke after a comprehensive negative evaluation. The patient was instructed to monitor ECG readings using a wearable digital gadget. Subsequently, her electrophysiologist validated the recorded data. Consequently, consumer wearable digital gadgets facilitate accurate diagnosis. Sukei et al. [77] illustrated the feasibility of developing machine learning models to predict emotional states via mobile sensor data, capable of accommodating heterogeneous data with significant missing values. Such models might serve as important instruments for clinicians to evaluate patients' emotional states. Additional study is advised to address sparse and lost tagged data, enabling future efforts to concentrate on the development of more novel models.

The widespread occurrence of SARS-CoV-2 has led to the global COVID-19 pandemic, resulting in advancements in wearable technologies that assess physiological changes in biometrics and provide online active patient monitoring [78]. Bogu and Snyder [79] proposed that wearable sensor data may serve as indicators for the early prediction of COVID-19. Furthermore, ongoing real-time research utilizing wearables in COVID-19 cases will enhance understanding of clinical features often overlooked by users and validated through laboratory investigations, thereby advancing knowledge pertinent to tracking and detecting COVID-19 outbreaks. Artificial intelligence using predictive models with machine learning and big data can forecast the evolution of certain illnesses, including diabetic nephropathy, and diagnosis SARS-CoV-2 infection in solid organ donation [80].

5. Drawbacks of Artificial Intelligence in Healthcare

Extensive datasets are essential for machine learning and deep learning models to accurately classify or predict diverse activities. Nonetheless, the healthcare sector has a complex issue regarding data accessibility, since patient records are personal, and healthcare organizations often exhibit reluctance to share health data. Furthermore, data are not immediately accessible when an algorithm is first performed with them. ML-based systems may continuously improve as more data is added to their training set; yet, achieving this is challenging owing to internal corporate opposition. Furthermore, AI-driven apps have concerns about data security and privacy. Hackers often target health records during data breaches due to their importance and susceptibility. Therefore, it is essential to maintain the confidentiality of health records [62].

Moreover, the overfitting problem arises when the algorithm assimilates the relationships between patient attributes and outcomes. This issue arises from several factors influencing the results, leading the algorithm to provide erroneous predictions. Data leaking is a significant issue that refers to AI's capacity to forecast events outside the reduced training dataset when the algorithm achieves enhanced predictive accuracy [63-65]. Moreover, deep learning algorithms are less adept at providing strong justifications for their predictions. An algorithm has challenges in securing legal protection when its suggestions fail. It complicates specialists' understanding of the relationship between the facts and their projections. The opacity of AI technologies may cause the public to lose confidence in healthcare systems [66].

The healthcare workers may apprehend AI in healthcare, perhaps diminishing their roles and supplanting them. Concurrently, they need re-engineering. Another concern about AI is the financial burden associated with the time and money allocated to educate healthcare professionals to effectively use AI [61]. In healthcare, inadequate experimental data validating the performance of AI-based pharmaceuticals in scheduled clinical trials poses a significant obstacle to the effective use of AI. AI research has mostly been conducted in non-clinical settings. Consequently, generalizing the results may be challenging. Likewise, institutions exhibit uncertainty and hesitance in implementing AI-based solutions due to insufficient empirical evidence and the substandard quality of research [67]. Additional drawbacks of AI include the substantial expenses associated with developing AI-driven applications, fostering human complacency, inducing unemployment by substituting monotonous labor with AI, and the absence of emotional intelligence and creativity in machines [68].

6. Conclusions

Artificial intelligence technology is used across several healthcare applications. These technologies have been designed to enhance medical imaging and diagnostic services, combat the pandemic, facilitate virtual patient care, improve patient engagement and adherence to treatment regimens, alleviate the administrative workload on healthcare professionals, promote drug and vaccine innovation, monitor patient compliance with exercise regimens, and conduct gait analyses utilized in technology-assisted rehabilitation. Nonetheless, AI encounters several technological, ethical, and governance issues as it advances in healthcare. It presents concerns about data security and privacy due to its utilization of sensitive and personal information governed by regulatory regulations.

The use of AI in tackling difficulties may be constrained by the quality of available health data and AI's inability to embody certain human traits, such as compassion. AI is more advantageous when operating effectively,yet it cannot replace the human ties that constitute teams. Human activities like collaboration and team management are unattainable objectives since robots are incapable of establishing a connection with people. A primary problem for the future administration of AI technologies will be to ensure that AI is created and deployed in alignment with human interests while considering technological, ethical, and social dimensions. This work contributes to the current literature on the use of AI in medical imaging and diagnostics, virtual patient care, medical research and drug development, patient engagement and adherence, rehabilitation, and other administrative functions. This is the most recent update in the literature about the ethical, social, governance, and technological problems encountered by healthcare professionals in the use of AI in healthcare.

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تأثير التقنيات الصحية الرقمية والذكاء الاصطناعي على تعزيز أنظمة الرعاية الصحية الوقائية مراجعة شاملة

الملخص

الخلفية:أدت التكاليف المتزايدة للرعاية الصحية، التي تفاقمت بسبب جائحة كوفيد -19، إلى تسليط الضوء على الحاجة الملحة لإيجاد حلول مبتكرة في الأنظمة الصحية العالمية . مع تزايد الأمراض المزمنة وشيخوخة السكان، أصبح من الضروري تطوير استراتيجيات رعاية وقائية معززة تعتمد على التكنولوجيا.

الطرق:تستعرض هذه المراجعة الأدبيات الحالية حول دور التقنيات الصحية الرقمية (DHTs) والذكاء الاصطناعي (AI) في الرعاية الصحية الوقائية. يتم تحليل وسائل مختلفة، بما في ذلك الصحة المتنقلة، والطب عن بعد، والأجهزة القابلة للارتداء، وتأثيرها على إدارة الأمراض، ومشاركة المرضى، وإمكانية الوصول إلى الرعاية الصحية.

النتائج:تشير النتائج إلى أن التقنيات الصحية الرقمية تسهم بشكل كبير في تحسين الرعاية الصحية الوقائية من خلال تمكين الكشف المبكر ومراقبة الأمراض المزمنة . كما يعزز الذكاء الاصطناعي اتخاذ القرارات من خلال تقنيات التصوير المتقدمة والتحليلات التنبؤية، مما يؤدي إلى تشخيصات أكثر دقة وخطط علاج مخصصة. ومع ذلك، تبقى التحديات المتعلقة بخصوصية البيانات، والفجوة الرقمية، والحاجة إلى أطر تنظيمية قوية قضايا حرجة يجب معالجتها.

الخلاصة:يوفر دمج التكنولوجيا في الرعاية الصحية الوقائية آفاقاً واعدة لتحسين نتائج المرضى وكفاءة الأنظمة الصحية . ومع ذلك، فإن معالجة الاعتبارات الأخلاقية وضمان الوصول العادل إلى هذه التقنيات أمر ضروري لتحقيق أقصى استفادة منها . يجب أن تركز الأبحاث المستقبلية على تطوير استراتيجيات شاملة لتجاوز الحواجز الحالية وضمان توافق التطورات التكنولوجية مع مبادئ الرعاية التي تركز على المريض.

الكلمات المفتاحية:الرعاية الصحية الوقائية، التقنيات الصحية الرقمية، الذكاء الاصطناعي، إدارة الأمراض المزمنة، إمكانية الوصول إلى الرعاية الصحية.