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Digital Disruption in Healthcare: What It Means for the NHS

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KEYWORDS

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This paper examines the transformative impact of digital technologies on healthcare systems, with a specific focus on the NHS. While earlier waves of medical innovation developed gradually over decades, the current digital disruption—driven by artificial intelligence, big data, genomics, and connected health devices—is unfolding at a much faster pace, reshaping how care is delivered, accessed, and organized. The paper traces the historical trajectory of health technologies, identifies key enabling innovations, and analyzes their maturity and readiness for adoption. It explores how digital tools are improving clinical outcomes, altering workforce structures, and influencing health expenditures. At the same time, the paper highlights the regulatory, ethical, and governance challenges posed by these technologies, including concerns around data use, algorithmic transparency, and equity. It argues for the urgent need to modernize regulatory frameworks and health technology assessment methods to keep pace with innovation. In doing so, it calls for anticipatory, adaptive, and inclusive approaches that support responsible innovation while safeguarding public trust and sustainability in the NHS and beyond.
Keywords: Health technologies, Innovation, Artificial intelligence, Healthcare delivery, Regulation and health economics.
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Discussion Paper Series

Digital Disruption in Healthcare: What It Means for the NHS

Discussion paper n. 20/2025

Vincenzo Atella (a), Lorenzo Chiari (b): (a) University of Roma Tor Vergata; (b) University of Bologna

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Digital Disruption in Healthcare: What It Means for the NHS

Authors:

Vincenzo Atella and **Lorenzo Chiari**[1]

Abstract

This paper examines the transformative impact of digital technologies on healthcare systems, with a specific focus on the NHS. While earlier waves of medical innovation developed gradually over decades, the current digital disruption—driven by artificial intelligence, big data, genomics, and connected health devices—is unfolding at a much faster pace, reshaping how care is delivered, accessed, and organized. The paper traces the historical trajectory of health technologies, identifies key enabling innovations, and analyzes their maturity and readiness for adoption. It explores how digital tools are improving clinical outcomes, altering workforce structures, and influencing health expenditures. At the same time, the paper highlights the regulatory, ethical, and governance challenges posed by these technologies, including concerns around data use, algorithmic transparency, and equity. It argues for the urgent need to modernize regulatory frameworks and health technology assessment methods to keep pace with innovation. In doing so, it calls for anticipatory, adaptive, and inclusive approaches that support responsible innovation while safeguarding public trust and sustainability in the NHS and beyond.

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1. Introduction[2]

Health is central to individual well-being and societal advancement, yet it was not until the mid-20th century that economists began exploring its economic impacts. At that time, health standards in affluent countries were much lower than they are today, though significantly better than in the early 1900s. For example, in 1900, approximately 18% of newborn males in the U.S. did not survive their first year, a rate comparable to that of 63-year-old adults by 2000 (Topel, 2017). A similar pattern was seen in Europe, where child mortality dropped from double digits in 1900 to just 0.5% in industrialized nations by 2000 (Atella, Francisci & Vecchi, 2017). Over the past century, life expectancy at birth has significantly increased thanks to various factors. These factors encompass decreased infant mortality rates, higher living standards, healthier lifestyles, improved education, and advancements in healthcare and medicine. For example, advancements in sanitation and health technologies, particularly vaccines and antibiotics, played a crucial role in combating infectious diseases (Alsan et al., 2018), which decreased infant mortality rates.

Since the end of WWII, technological progress in the healthcare sector has driven a continuous increase in global life expectancy. Official data shows that, on average, in Europe, life expectancy has grown by more than two years each decade since the 1960s (Eurostat, 2025). More recently, these gains have been even larger. According to the World Health Organization (WHO), life expectancy at birth rose from 66.8 years in 2000 to 73.1 years in 2019, marking a gain of over six years. In Africa, life expectancy increased by 10.6 years, rising from 53 years in 2000 to 63.6 years in 2021. The role of pharmaceutical innovation in reducing premature mortality, especially in cancer treatment, underscores that medical progress is a key driver of human longevity (Lichtenberg, 2014, 2016, 2017). EUROSTAT projects that life expectancy in the European Union will reach 89.1 years for women and 84.6 for men by 2060, continuing the trend of extended lifespans.

Medical innovations have powered massive improvements in healthcare, transforming fatal conditions into manageable ones, expanding access to care, and revolutionizing clinical procedures. Premature infants, for instance, who had minimal survival chances before the 1950s, now benefit from life-saving technologies such as mechanical ventilators and neonatal intensive care units. These advancements have added roughly 12 years to the life expectancy of low-birthweight infants (Skinner, 2013). Cardiac care has also come a long way. From basic medications like beta-blockers and aspirin to advanced procedures like coronary bypass surgeries and implantable defibrillators, these innovations have slashed heart attack mortality in the United States by almost 50% between 1980 and 2000 (Skinner, 2013).

Until around the early 2010s, technological innovation in healthcare followed a relatively gradual path. Major breakthroughs—such as advanced imaging systems, minimally invasive surgical techniques, and new generations of pharmaceuticals—were undeniably transformative, but they evolved over decades through incremental improvements and long development cycles. This slower pace allowed time for adaptation across healthcare systems, regulatory frameworks, and medical training (Blumenthal & Dixon, 2012; Wachter, 2015; Dorsey & Topol, 2016). In stark contrast, the current wave of innovation is advancing at an unprecedented speed, catalyzed by the sweeping digital transformation of healthcare. Today, progress is being driven by the rapid convergence of artificial intelligence, big data analytics, wearable biosensors, telemedicine, personalized genomics, and digitally enabled care processes. These technologies are not merely extending the capabilities of medicine; they are redefining the entire landscape of how care is delivered, analyzed, and experienced. Machine learning algorithms can now detect diseases such as diabetic retinopathy or certain cancers with diagnostic accuracy that rivals, or even surpasses, that of experienced clinicians

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(Topol, 2019a,b). Genomic sequencing, which once cost billions and took years to perform, can now be completed in days at a fraction of the cost, enabling a new era of precision medicine. The current digital revolution in medicine marks a pivotal turning point in the trajectory of technological innovation within the healthcare sector. Unlike previous waves of medical advancement, today's progress is not only redefining what is medically possible but also drastically accelerating the speed at which innovation reaches clinical practice. This shift signals a fundamental change in how we will understand, implement, and govern medical technology in the years to come.

This exponential acceleration also signals a groundbreaking change in the rhythm of medical progress. The boundaries between biomedical research, clinical practice, and digital technology are becoming increasingly porous, allowing innovations to move from concept to bedside with unprecedented speed. Moreover, this new landscape is not only about the tools we use but also about a paradigm shift in how healthcare systems operate: from reactive care to predictive and preventive models; from generalized treatments to personalized interventions; and from episodic visits to continuous, data-driven patient monitoring. The implications of this shift are profound. As we stand on the brink of an era where artificial intelligence co-pilots diagnosis and treatment decisions and where vast health datasets inform policy and research in real-time, the question is no longer *if* digital technology will redefine medicine but *how quickly and how responsibly* it will be integrated. The digital revolution may not appear just as another chapter in the story of medical progress—it may be a rewriting of the narrative itself.

The need for this transformation is further amplified when considering the biopsychosocial model of health, which recognizes the intricate interplay between biological, psychological, and social factors in determining an individual's well-being (Engel, 1978).[3] This holistic perspective necessitates healthcare solutions that address the multifaceted needs of patients, extending beyond purely biological interventions to encompass their mental and social contexts. In the digital age, the influence of technology itself has become a significant determinant of health experiences and outcomes. Consequently, a "biopsychosocial-digital" approach has been proposed, advocating for the integration of the digital dimension into the traditional biopsychosocial framework (Ahmadvand et al., 2018). This expanded model acknowledges the profound impact of digital engagement on patients' choices, behaviors, and overall health journey. Digital tools present unique opportunities to collect and analyze data related to all three domains of the biopsychosocial model, enabling a more nuanced and personalized approach to care. By leveraging technologies that monitor biological parameters, support mental well-being, and facilitate social connections, healthcare can move towards a more comprehensive strategy for measuring, preserving, and improving the health and quality of life of individuals. This includes recognizing the importance of an individual's ability to engage in activities and participate in society as key indicators of their overall well-being.

This transformation is inextricably linked to one of the most critical challenges confronting contemporary healthcare systems: the persistent increase in costs. While technological advancements have undeniably revolutionized medical practice, leading to improvements in diagnostics, treatments, and patient outcomes, they have also contributed substantially to the rising costs of healthcare. In contrast to other sectors where technological innovation typically reduces costs while simultaneously improving outcomes, in healthcare, these advancements often yield both enhanced outcomes and increased expenditures (often through higher prices). The introduction of cutting-edge medical technologies often entails substantial expenses, encompassing research and development, acquisition, maintenance, and the specialized training required for healthcare professionals. Moreover, the availability of advanced technologies can lead to increased utilization, sometimes extending beyond medically necessary applications, further driving up costs. Consequently, healthcare expenditures have grown faster than in any other economic sector, especially since

[3] The biopsychosocial model has transformed healthcare by emphasizing the connection between biological, psychological, and social factors in health and disease, providing a more holistic approach than the traditional biomedical model. It is particularly useful for chronic illnesses, pain disorders, and mental health. However, challenges like reductionist medical education, insufficient interdisciplinary collaboration, and financial constraints hinder its implementation (Seyed Alitabar, 2025).

the latter decades of the 20th century. These cost increases have been driven by factors such as the development of treatments for previously untreatable diseases, the expansion of treatment access, and enhancements in treatment quality (Cutler, McClellan& Newhouse, 1998; Eggleston et al., 2011).

The cost implications of new technologies depend on the type of innovation. Key considerations include whether the new treatment complements or substitutes existing ones, whether it is a standalone intervention or used in conjunction with others, and how it affects overall treatment costs. Additionally, the degree of dissemination and population coverage is critical. Technological advancements often result in broader applications, which can increase total spending even if individual unit costs decline (Weisbrod, 1991; Cutler & Huckman, 2003). Furthermore, the temporal realization of health and economic benefits must be accounted for, as some technologies yield cost savings only in the long term. Many technologies embody several of these characteristics simultaneously, complicating the assessment of their overall financial impact. One of the major challenges in this domain is accurately capturing quality improvements embedded in new technologies. As Rosen and Cutler (2007) note, while some evaluations suggest reasonable aggregate productivity growth in healthcare, others highlight significant inefficiencies.

As digital tools become embedded across diagnostics, therapeutics, prevention activities, workforce management, and patient interaction, they challenge the economic models and institutional frameworks on which many national health systems—such as the NHS—are based. In this context, economic research is increasingly called upon to assess not only the effects of these technologies on efficiency and outcomes but also their distributional consequences, regulatory implications, and cost dynamics. This paper explores the economic dimensions of health system innovation considering the recent digital transformation. Drawing on developments in enabling technologies, digital health applications, and regulatory challenges, it offers a structured assessment of how innovation is reshaping healthcare systems and policy trade-offs.

The paper is organized into nine sections. Section 2 provides a historical overview of the evolution of medical technologies, tracing the transition from public health interventions and pharmaceuticals to highly specialized and resource-intensive innovations to digital technologies. Section 3 presents a horizon scanning exercise and offers a taxonomy of emerging digital technologies with the potential to transform healthcare. Section 4 delves into the specific impact of artificial intelligence on healthcare systems, examining its role in clinical decision-making, resource optimization, and workforce planning. Section 5 expands the scope of analysis to a broader set of digital applications—such as telemedicine, digital therapeutics, and point-of-care diagnostics—and discusses how they are reshaping healthcare delivery and patient experience. Section 6 provides a maturity assessment of digital health solutions, evaluating the degree to which different technologies are ready for widespread adoption based on technical, regulatory, and systemic criteria. Section 7 discusses the broader impacts of these technologies on healthcare outcomes and the organization of the workforce, including their potential to improve productivity and reshape professional roles. Section 8 turns to the regulatory dimension, analyzing how institutions are managing the tension between rapid innovation and the requirements of safety, equity, and cost-effectiveness. Section 9 considers the economic implications of technological adoption for healthcare expenditure and explores whether digital innovation might alter the traditional cost-growth trajectory of health systems. Finally, Section 10 concludes by outlining future directions for research and policy, with an emphasis on anticipatory regulation, investment in digital infrastructure, and the need for coherent strategies to integrate innovation into health system reform.

2. The Evolution of Medical Technologies: Expected Innovations in Healthcare Services, Processes, and Delivery Models

In their 2019 article, "New Technologies and Costs," published in the *Oxford Research Encyclopedia of Economics and Finance*, Atella and Kopinska provided a comprehensive synthesis of the evolution of medical technologies and their impact on healthcare systems, with particular attention to cost dynamics and

sustainability. This foundational work outlined the interplay between innovation, regulation, and expenditure in health systems like the UK's National Health Service (NHS), offering a crucial baseline for understanding the challenges and opportunities posed by new technologies in healthcare up to the end of the 2010s.

The authors traced the trajectory of technological change from the early public health revolutions of the 20th century—characterized by gains in sanitation, nutrition, and infectious disease control—to the pharmaceutical and procedural innovations of the post-war decades. The development and diffusion of antibiotics, vaccines, surgical techniques, intensive care, and pharmaceuticals led to sharp improvements in population health and longevity. These innovations were associated mainly with systemic public health gains and, in many cases, provided cost-effective solutions to widespread clinical problems.

However, from the 1980s onward, the authors noted a shift in the character of technological change. Innovations became increasingly specialized, sophisticated, and resource-intensive. In particular, the rise of biologic drugs, advanced diagnostic imaging, minimally invasive procedures, and, more recently, gene therapies and digital health tools marked a departure from earlier innovations that were typically mass-distributable and cost-scaling. These new technologies promised better patient outcomes but often did so at substantially higher costs, requiring significant investments in infrastructure, workforce training, and system reorganization.

Atella and Kopinska (2019) identified five main domains of technological innovation: pharmaceutical products, medical and surgical procedures, medical devices, support systems (such as telehealth and electronic records), and precision medicine. Each domain displayed its own set of cost, regulatory, and evaluation challenges. For instance, the pharmaceutical sector increasingly relied on targeted therapies—such as biologics and monoclonal antibodies—that, while clinically effective, drove up the costs of care. Meanwhile, surgical and procedural innovations often enabled faster recovery and reduced inpatient time but introduced equity and access issues due to uneven availability and skill requirements.

Since the publication of Atella and Kopinska's work, the pace of medical technological development has accelerated dramatically. The last decade has witnessed not only a continuation of earlier trends but also the emergence of entirely new technological trajectories. The COVID-19 pandemic catalyzed rapid advances in digital health infrastructure, mRNA vaccine platforms, remote care, and real-time health data analytics. Artificial intelligence and machine learning have moved beyond the experimental stage to influence diagnostics, clinical decision-making, and health system management. Meanwhile, wearable devices, home-based monitoring, and personalized medicine have become increasingly mainstream. These developments suggest that the dynamics described up to 2019 have shifted substantially. Some technological domains have evolved far beyond expectations, while others have seen entirely new directions emerge.

The continued advancement and integration of new technologies are now expected to drive significant innovations across various aspects of healthcare, extending beyond just the development of new products to encompass novel services, transformative processes, innovative care pathways, and new healthcare delivery models (OECD, 2019), to also meet the demands of an evolving patient demographic and drive progress in public health systems (Cecconi et al., 2025). Some of these anticipated advancements include (OECD, 2019; Goldsack et al., 2020; Patel et al., 2023):

- New Services: Future healthcare is likely to see the emergence of AI-powered personalized health coaching and wellness programs that adapt to individual data and preferences. Remote rehabilitation services delivered through VR/AR platforms will allow patients to receive therapy conveniently in their own homes. Virtual consultations with medical specialists in remote or underserved areas will become more commonplace, significantly improving access to expert care.
- Transformative Processes: AI-assisted diagnostics are expected to become increasingly sophisticated, enabling faster and more accurate disease detection, particularly in fields like medical imaging analysis.

The automation of data collection and analysis in clinical research will accelerate the pace of medical discovery. Robotic process automation will streamline administrative tasks within healthcare organizations, freeing healthcare professionals to dedicate more time to direct patient care.

- Innovative Care Pathways: Integrated digital and in-person care models will likely become the norm, offering a hybrid approach that combines the convenience of remote monitoring and virtual consultations with the necessity of in-person examinations and procedures when required. Proactive and predictive healthcare, driven by continuous monitoring through wearable sensors and AI-powered risk assessment, will enable early interventions and the development of highly personalized prevention plans.
- Novel Healthcare Delivery Models: Decentralized clinical trials (DCTs), leveraging digital technologies to enable remote participation, are poised to become a more prevalent model for conducting clinical research, potentially leading to greater patient participation and the collection of more real-world data. Hospital-at-home models, supported by comprehensive remote monitoring, telehealth services, and AI-powered virtual assistants, will enable patients with certain acute conditions to receive high-quality care in the comfort of their own homes.

These digital transformations signal a paradigm shift in how healthcare is conceived, delivered, and experienced. For example, AI-driven triage systems in emergency departments are reducing wait times and optimizing resource allocation in real time. Predictive analytics platforms enable care teams to anticipate patient deterioration days before clinical signs emerge. Smart medication adherence tools, integrated with electronic health records, are improving outcomes in chronic disease management. Digital twins of patients—virtual replicas based on real-time data—are beginning to inform treatment simulations prior to intervention. These examples, which will be explored in more detail later in the chapter, illustrate how innovation is reconfiguring healthcare around proactive, patient-centered, and data-driven principles.

3. Horizon Scanning: Enabling Technologies Revolutionizing Healthcare

In the context of rapid technological change, shifting demographics, and evolving disease burdens, healthcare systems must become increasingly strategic and anticipatory in their planning. Horizon scanning has emerged as a critical tool for achieving this goal. Defined as a systematic process for identifying emerging trends, technologies, and potential threats before they become widely recognized or adopted, horizon scanning allows health systems to prepare proactively rather than reactively (National Academies of Sciences, Engineering, and Medicine, 2020).

In the healthcare sector, horizon scanning plays a key role in informing policy, research prioritization, and resource allocation. By monitoring early signals of innovation in fields such as biotechnology, artificial intelligence, personalized medicine, and digital health, it supports timely decision-making regarding health technology assessments (HTA), reimbursement models, and service redesign (Oortwijn et al., 2018). For example, many national HTA agencies in Europe, such as those coordinated through the European Network for Health Technology Assessment (EUnetHTA), have integrated horizon scanning into their early dialogue processes to inform future evaluations and guide the adoption of new technologies (EuroScan International Network, 2020).

For these reasons, we have run a horizon scanning exercise to understand what are the main technological trends that are nowadays pervading the healthcare sector, with the aim to anticipate disruptive developments and enable governments and health organizations to invest in infrastructure, workforce development, and regulatory frameworks that are aligned with future needs. Moreover, horizon scanning contributes to a more transparent and participatory planning culture. By incorporating multidisciplinary perspectives—spanning clinical, technological, social, and ethical domains—it promotes comprehensive foresight and builds

consensus around strategic priorities (Miles, 2010). In doing so, it supports the development of resilient health systems capable of adapting to complex and uncertain futures. As healthcare becomes more data-driven and interdependent with other sectors, such as technology and environmental planning, the systematic use of horizon scanning is becoming an essential component of sustainable health system governance. Its integration into national and institutional planning frameworks offers a path toward more agile, informed, and forward-looking healthcare decision-making.

The result of this exercise is summarized in Table 1, where we report a comprehensive overview of the current and future landscape of digital enabling technologies in healthcare, presenting a taxonomy to categorize these diverse innovations and exploring their applications, potential, market impact, and the challenges associated with their implementation. While there is often overlap and synergy between different technologies, this classification helps in understanding the distinct contributions and potential of each category. The categories covered include Connectivity & Infrastructure, Data & Analytics, Devices & Wearables, Advanced Technologies, Advanced Computing, and Digital Therapeutics & Interventions.

Table 1 - Taxonomy of Enabling Technologies in Healthcare

Category	Technology	Description	Current Applications in Healthcare	Future Potential in Healthcare
Connectivity & Infrastructure	Telemedicine & Telehealth	Provision of healthcare services remotely using telecommunications technology.	Virtual consultations, remote monitoring, telediagnosis, telementoring.	Seamless integration into hybrid care models, advanced telepresence, AI-assisted remote diagnostics.
	Mobile Health (mHealth)	Healthcare supported by mobile devices.	Wellness/fitness apps, medication reminders, remote data collection, patient portals.	Personalized health management apps, integration with wearables, chronic disease management.
	Internet of Medical Things (IoMT)	Network of connected medical devices and sensors.	Remote patient monitoring, connected medical devices in hospitals, asset tracking.	Real-time continuous monitoring, predictive alerts, connected hospitals, personalized treatment adjustments.
Data & Analytics	Electronic Health Records (EHRs)	Digital versions of patient charts.	Storing/accessing patient history, streamlining workflows, care coordination, basic analytics.	True interoperability, AI integration for decision support, population health management, patient data access.
	Big Data Analytics	Analysis of large and complex healthcare datasets.	Identifying trends, analyzing treatment outcomes, managing operations, public health surveillance.	Predictive modeling for outcomes, personalized medicine cohorts, clinical trial optimization, insights into health determinants.
	Artificial Intelligence (AI)	Computer systems performing tasks requiring human intelligence.	Medical image analysis, drug discovery assistance, potential diagnosis identification, administrative automation, chatbots.	Highly accurate/rapid diagnostics, personalized treatment plans, predictive analytics for risk, AI virtual assistants, robotic surgery enhancement.
	Machine Learning (ML) and Deep	Algorithms allowing systems to learn from data.	Predicting patient risk, analyzing genomic data, personalizing treatment protocols, improving	More sophisticated predictive models, continuous learning from real-world data, identifying

Category	Technology	Description	Current Applications in Healthcare	Future Potential in Healthcare
	Learning (DL)		diagnostic accuracy, clinical decision support.	complex patterns, adaptive therapeutic interventions.
	Natural Language Processing (NLP)	Enabling computers to understand human language.	Analyzing clinical notes, extracting information from text, powering medical chatbots.	Automated medical literature summarization, sophisticated conversational agents, automated clinical documentation, analyzing patient narratives.
Devices & Wearables	Wearable Devices	Electronic devices worn on the body collecting health data.	Tracking activity/heart rate/sleep, consumer health monitoring, some remote patient monitoring.	Continuous passive monitoring of wide parameters, seamless integration with healthcare platforms, early detection, diagnostic capabilities.
	Connected Medical Devices	Medical devices with connectivity features.	Connected glucose meters, smart blood pressure cuffs, remote monitoring of infusion pumps/inhalers.	Real-time adjustment based on data/AI, predictive alerts, enhanced data sharing, closed-loop systems.
Advanced Technologies	Blockchain	Decentralized, distributed ledger technology.	Securely storing/sharing patient data, supply chain management, professional credential verification, clinical trial data management.	Interoperable patient-controlled records, healthcare data marketplaces, streamlined claims processing.
	Augmented Reality (AR)	Overlaying digital information onto the real world.	Surgical planning/visualization, medical training/education, assisting nurses (e.g., vein finding).	Image-guided surgery with real-time overlays, interactive anatomy learning, remote expert guidance, AR rehabilitation.
	Virtual Reality (VR)	Creating immersive, interactive simulated environments.	Medical training simulations, pain management/therapy, exposure therapy, patient education.	Highly realistic surgical training, immersive rehabilitation, VR telemedicine, advanced pain/psychological therapies.
	Robotics	Use of robots to perform tasks.	Surgical robots, automated medication dispensing, laboratory automation, internal logistics.	More advanced/autonomous surgical robots, increased role in direct patient care, sophisticated automated logistics.
	3D Printing	Creating three-dimensional objects layer by layer.	Patient-specific prosthetics/implants, anatomical models for planning/training, customized medical devices/guides.	Bioprinting tissues/organs, on-demand personalized medications, point-of-care device printing.

Category	Technology	Description	Current Applications in Healthcare	Future Potential in Healthcare
	Digital Twins	Virtual replicas updated with real-time data.	Simulating organs/systems, optimizing hospital workflows/resources.	Patient-specific digital twins for personalized treatment simulation, optimizing healthcare networks, revolutionizing clinical trials.
Advanced Computing	High-Performance Computing (HPC)	Use of supercomputers and parallel processing.	Processing large genomic datasets, molecular simulations for drug discovery, complex medical imaging analysis.	More sophisticated genomic analysis, accelerating drug discovery, advanced imaging analysis/reconstruction, large-scale public health modeling.
	Quantum Computing	Computing using quantum mechanics principles.	Research into drug discovery simulation, exploring optimization for complex healthcare problems (currently R&D).	Revolutionizing drug discovery/molecular simulation, highly personalized treatment planning, enhancing AI capabilities.
Digital Therapeutics & Interventions	Digital Therapeutics (DTx)	Software delivering evidence-based therapeutic interventions.	Managing chronic conditions (diabetes, mental health), substance abuse disorders.	Integration into clinical workflows, personalized/adaptive interventions, expansion to wider conditions, remote monitoring/adjustment.
	Digital Care Programs	Comprehensive digital platforms supporting patient care/management.	Remote monitoring programs, virtual rehabilitation, care coordination platforms, patient engagement tools.	Highly integrated/personalized care pathways, AI-powered coordination/support, remote management of complex conditions.

3.1. Connectivity & Infrastructure

Technologies in this category focus on enabling communication, data exchange, and service delivery across geographical distances and between different stakeholders in the healthcare ecosystem.

3.1.1. Telemedicine & Telehealth

Telemedicine and telehealth encompass the use of electronic information and telecommunications technologies to support and promote long-distance clinical healthcare, patient and professional health-related education, public health, and health administration. This includes a wide range of services such as virtual consultations, remote patient monitoring, transmission of medical images, and remote medical education.

Current Applications: Currently, telemedicine is widely used for routine consultations, follow-up appointments, managing chronic conditions, and providing access to specialists in remote or underserved areas (Ezeamii et al., 2024). It gained significant traction during the recent global pandemic, becoming an essential tool for maintaining access to care while minimizing physical contact. Telediagnosis, teleradiology, and telepathology are established applications that allow remote expert analysis of medical data.

Future Potential: The future of telemedicine involves seamless integration into hybrid care models, where virtual and in-person care are combined based on patient needs. Advanced telepresence technologies,

including high-definition video and haptic feedback, could enable more complex remote examinations and procedures. AI could be integrated to assist with remote diagnostics and triage, further increasing efficiency and accessibility. The expansion of 5G networks will provide the necessary bandwidth for more sophisticated telemedicine applications.

Quantitative Data: The global telemedicine market size was estimated to be valued at over $100 billion in recent years and is projected to grow significantly, with some reports predicting a compound annual growth rate (CAGR) of over 20% in the coming years (Grand View Research, 2024). The socio-economic impact includes reduced travel costs and time for patients, increased access to care for rural populations, and potentially lower healthcare costs by reducing hospital visits and admissions.

Open Challenges: Challenges include ensuring equitable access to necessary technology and internet connectivity, addressing regulatory and reimbursement complexities across different regions, maintaining data privacy and security during transmission, and ensuring the quality and effectiveness of remote consultations compared to in-person visits. Clinician training and patient acceptance also remain important factors.

3.1.2. Mobile Health (mHealth)

mHealth refers to the practice of medicine and public health supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices. It leverages the ubiquitous nature of mobile technology to provide health-related information, services, and data collection capabilities.

Current Applications: Current applications include a vast array of wellness and fitness apps, medication reminder apps, symptom checkers, remote data collection from connected devices, and mobile access to patient portals for viewing health records and scheduling appointments (Deniz-Garcia et al., 2023). mHealth is also used in public health campaigns and data collection for disease surveillance.

Future Potential: Future mHealth will be characterized by highly personalized health management through advanced apps that integrate data from multiple sources, including wearables, EHRs, and even genomic information. AI-powered mHealth apps could provide tailored health coaching, predict health risks based on user data, and offer just-in-time interventions. The role of mHealth in managing chronic diseases and promoting preventative care is expected to expand significantly.

Quantitative Data: The global mHealth market is a substantial segment of digital health, with market size estimates varying but generally in the tens of billions of US dollars in 2024 and strong projected growth, exhibiting a CAGR of 11.8% by 2032 (Fortune Business Insights, 2024). The socio-economic impact includes empowering individuals to take a more active role in managing their health, potentially leading to improved health outcomes and reduced healthcare utilization for preventable conditions.

Open Challenges: Key challenges include ensuring the accuracy and reliability of health information provided by apps, addressing data privacy and security concerns related to sensitive personal health data collected by mobile devices, regulatory oversight of medical-grade mHealth applications, and ensuring usability and accessibility across diverse user populations.

3.1.3. Internet of Medical Things (IoMT)

IoMT refers to the connected infrastructure of medical devices, software applications, and health systems and services. It involves the use of internet-connected devices to collect and transmit health data, enabling remote monitoring, tracking, and management of patients and medical assets.

Current Applications: Current applications include remote patient monitoring devices for conditions like diabetes (connected glucose meters), cardiovascular disease (wearable ECG monitors), and respiratory

disorders (smart inhalers). IoMT is also used to track medical equipment within hospitals, manage inventory, and monitor environmental conditions in healthcare facilities (Huang, Wang et al., 2023).

Future Potential: The future of IoMT involves real-time, continuous, and passive monitoring of a wide range of physiological parameters through advanced sensors and wearables. This will enable early detection of health deterioration, predictive alerts for critical events, and personalized adjustments to treatment plans based on continuous data streams. IoMT will also play a crucial role in connected hospitals, optimizing workflows and patient care through interconnected devices and systems.

Quantitative Data: The IoMT market is experiencing rapid growth, with market size estimates in the tens of billions of US dollars and high projected CAGRs (38.5%) (Fortune Business Insights, 2025a). The socio-economic impact includes improved management of chronic diseases, reduced hospital readmissions, increased efficiency in healthcare operations, and the potential for proactive health interventions based on continuous data.

Open Challenges: Significant challenges include ensuring the security of connected medical devices against cyber threats, managing the massive volume of data generated by IoMT devices, ensuring interoperability between different devices and platforms, addressing regulatory hurdles for connected medical devices, and establishing clear protocols for responding to data-driven alerts and insights.

3.2. Data & Analytics

This category focuses on the collection, storage, processing, analysis, and interpretation of healthcare data to generate insights and support decision-making.

3.2.1. Electronic Health Records (EHRs)

EHRs are digital versions of patients' paper charts containing medical history, diagnoses, medications, treatment plans, immunization dates, allergies, radiology images, and laboratory and test results. They are designed to be shared across different healthcare settings.

Current Applications: EHRs are fundamental to modern healthcare administration and delivery. They are used for storing and accessing patient information, streamlining clinical workflows, improving communication and coordination among healthcare providers, and supporting basic data analytics for reporting and quality improvement (Shen et al., 2025). Patient portals linked to EHRs allow patients to access their health information and communicate with providers.

Future Potential: The future of EHRs lies in achieving true interoperability, allowing seamless and secure exchange of patient data across all healthcare providers and even between different countries. EHRs will be integrated with advanced AI and machine learning algorithms to provide real-time clinical decision support, identify patients at risk, and personalize treatment recommendations. They will also serve as a rich data source for research and public health initiatives.

Quantitative Data: The global EHR market is substantial, valued at about $30 billion in 2024, with steady growth expected (CAGR of about 5% from 2025 to 2033) as adoption rates increase and systems become more sophisticated (Business Research Insights, 2024). The socio-economic impact includes improved care coordination, reduced medical errors due to better access to patient information, increased efficiency in administrative tasks, and the potential to leverage aggregated data for research and public health.

Open Challenges: Major challenges include achieving true interoperability between disparate EHR systems, addressing data privacy and security concerns related to the centralization of sensitive patient information, the high cost of implementation and maintenance, usability issues that can lead to clinician burnout, and ensuring data quality and standardization.

3.2.2. Big Data Analytics

Big Data Analytics involves the examination of large and complex datasets to uncover hidden patterns, correlations, trends, and other insights. In healthcare, these datasets can come from various sources, including EHRs, genomic data, medical imaging, wearable devices, and social media.

Current Applications: Currently, big data analytics is used to identify trends in patient populations, analyze the effectiveness of different treatments, manage hospital operations and resource allocation, predict patient demand, and support public health surveillance and outbreak prediction (Khan et al., 2022).

Future Potential: Future applications will include more sophisticated predictive modeling for individual patient outcomes, identifying specific patient cohorts for highly personalized medicine approaches, optimizing clinical trial design and recruitment, and gaining deeper insights into the social and environmental determinants of health by integrating diverse data sources. Real-time analytics will enable proactive interventions.

Quantitative Data: The global healthcare analytics market is valued at tens of billions of US dollars and is projected to reach more than 120 billion by 2033, growing at a CAGR of 24.3% from 2024 to 2033, driven by the increasing availability of health data and the need for data-driven decision-making (Allied Market Research, 2024). The socio-economic impact includes the potential for improved patient outcomes through personalized interventions, cost savings through optimized operations and resource allocation, and advancements in medical research and public health strategies.

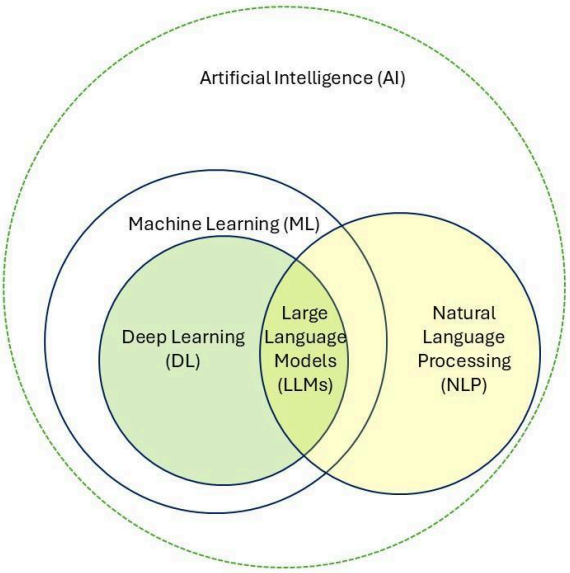
Open Challenges: Challenges include managing and processing the sheer volume, velocity, and variety of healthcare data, ensuring data quality and standardization across disparate sources, addressing data privacy and security concerns when working with large datasets, the need for skilled data scientists and analysts in healthcare settings, and the ethical considerations related to using patient data for analytics.

3.2.3. Artificial Intelligence (AI)

AI refers to the ability of machines to perform tasks autonomously, mimicking human cognitive functions, namely, learning and problem-solving (Jiang et al., 2017; Topol, 2019a,b).

Within the healthcare domain, subfields such as machine learning and deep learning are particularly relevant. Machine learning (ML), a subset of AI, leverages vast datasets to discern patterns and progressively enhance their predictive accuracy. Deep learning (DL), a further subset of ML characterized by its intricate, multi-layered neural networks, has demonstrated a remarkable capacity for understanding complex language structures and contextual nuances. Natural Language Processing (NLP) refers to AI techniques that enable machines to understand and generate human language. At the intersection of DL and NLP lie Large Language Models (LLMs), which leverage deep learning architectures to process and produce human-like language. The Venn diagram in **Figure 1** illustrates the hierarchical and overlapping relationships between major areas within AI. The figure highlights how LLMs draw on advances in both deep learning and language understanding. LLMs are an example of Generative AI (GenAI). However, not all Generative AIs are LLMs, including also, among others, Generative Adversarial Networks (GANs), mainly for images/videos, and generative models specifically designed to create novel chemical structures.

Figure 1 - Conceptual relationships among key subfields of Artificial Intelligence.



Source: Our elaboration.

Current Applications: AI is increasingly central to the evolution of modern medicine (OECD, 2023). AI is currently being applied in medical image analysis (e.g., detecting anomalies in X-rays, CT scans, and MRIs), speeding up drug discovery and development by analyzing vast biological datasets, identifying potential diagnoses based on patient symptoms and history, and automating administrative tasks like scheduling and billing (Yu et al., 2018; Mak & Pichika, 2019; Kanakia et al., 2025; Morone et al., 2025). AI-powered chatbots are also used for initial patient interaction and information provision (Bajwa et al., 2021).

Future Potential: The future of AI in healthcare holds immense promise, including highly accurate and rapid diagnostic tools, personalized treatment plan generation based on individual patient profiles (including genomics), predictive analytics for identifying patients at high risk of developing certain conditions or experiencing adverse events, and AI-powered virtual assistants that can provide comprehensive patient support and even perform initial triage. AI could also revolutionize robotic surgery with increased precision and autonomy.

Quantitative Data: The global AI in the healthcare market is a rapidly expanding sector, valued in the billions of US dollars, and projected to grow at a very high CAGR of 38.62% from 2025 to 2030 (Grand View Research, 2024). The socio-economic impact includes the potential for earlier and more accurate diagnoses, the development of more effective and personalized treatments, increased efficiency for healthcare professionals by automating routine tasks, and potentially reducing healthcare costs in the long run.

A recent Deloitte research (Deloitte, 2024) reveals that applying AI, particularly GenAI, in pharmaceutical R&D can generate $5–7 billion in value over five years for a top 10 biopharma company. R&D holds the greatest potential, contributing 30–45% of this value. This is achieved through the acceleration of drug development processes and substantial cost reductions. GenAI can significantly improve the modeling of proteins and other biomolecules, which is crucial in identifying and validating new drug candidates at a much faster pace. By analyzing vast repositories of scientific data, GenAI supports the discovery of novel drug targets and illuminates previously unknown connections between diseases. These insights are then tested and validated through laboratory experiments, demonstrating a highly productive synergy between AI-generated analysis and the insights of human researchers.

Open Challenges: Significant challenges include ensuring the explainability and transparency of AI decision-making processes (the "black box" problem), addressing potential biases in AI algorithms that

could lead to health disparities, regulatory approval and validation of AI-based medical devices and diagnostics, ensuring data privacy and security when using large datasets for AI training, and the ethical considerations surrounding the use of AI in critical healthcare decisions. Despite significant advances in AI research, the deployment and adoption of AI technologies in clinical practice remain limited, pending the development and implementation of trustworthy AI tools (Lekadir et al., 2025).

3.2.4. Machine Learning (ML) and Deep Learning (DL)

Machine Learning, a subset of AI, focuses on developing algorithms that allow computer systems to learn from data without being explicitly programmed. Deep learning is itself a subset of machine learning that uses multi-layered neural networks to learn representations from large amounts of data automatically. In healthcare, this involves training models on medical datasets to identify patterns, make predictions, and improve performance over time (Esteva et al., 2019; Topol, 2019a,b).

Current Applications: ML is currently used to develop algorithms for predicting patient risk factors (e.g., for developing chronic diseases or readmission), analyzing genomic data to identify genetic predispositions, personalizing treatment protocols based on patient characteristics and historical data, and improving the accuracy of diagnostic tools through pattern recognition (Deo, 2015; Rajkomar et al., 2019; Zeleke et al., 2023). DL models, in particular, have shown strong performance in medical imaging, avoiding delayed diagnosis or misdiagnosis of acute myocardial infarction (AMI), enabling radiologists to identify anomalies such as tumors or fractures with near-human or even superior accuracy (Litjens et al., 2017; Liu et al., 2021; Huang, Yang et al., 2023).

Future Potential: Future ML applications will involve more sophisticated predictive models that can anticipate health events with greater accuracy, continuous learning from real-world patient data to refine diagnoses and optimize treatments in real-time, identifying subtle and complex patterns in large biological and clinical datasets that are imperceptible to humans, and developing adaptive therapeutic interventions that adjust based on patient response. Deep learning, in particular, holds promise for revolutionizing image-based diagnostics, enabling nuanced analysis of radiological, pathological, and genomic images.

Quantitative Data: As a core component of AI, ML—including DL—represents a significant and expanding area within the healthcare market, contributing substantially to the overall AI market size and growth. The socio-economic impact reflects AI's broader potential: improved predictive accuracy, personalized interventions, and the ability to extract valuable knowledge from increasingly complex and heterogeneous healthcare data.

Open Challenges: Key challenges include the need for large, high-quality, and unbiased datasets to train ML models, ensuring interpretability and transparency—particularly for DL architectures, which are often considered "black boxes"—addressing overfitting and generalization limits, managing the intensive computational demands of deep neural networks, and confronting the ethical and legal implications of using predictive models in clinical decision-making, especially in terms of bias, equity, and accountability (Obermeyer et al., 2019). Moreover, disparities in the datasets used to train AI systems may inadvertently perpetuate existing inequities in healthcare delivery (Wiens et al., 2019). To mitigate these concerns, it is essential to adopt robust strategies for data collection, validation, and continuous model updating. This includes curating diverse and representative datasets and ensuring that algorithms are periodically retrained to reflect evolving clinical knowledge and patient populations (Chen et al., 2020). Post-deployment monitoring and algorithm auditing are critical not only for performance optimization but also for addressing ethical concerns, such as accountability and transparency (Morley, Floridi et al., 2020).

3.2.5. Natural Language Processing (NLP)

NLP is a field of AI that focuses on enabling computers to understand, interpret, and generate human language. In healthcare, this is particularly relevant for processing and analyzing unstructured text data found in clinical notes, reports, and medical literature.

Current Applications: NLP plays a pivotal role in unlocking insights from unstructured data—such as clinical notes, patient conversations, and EHR entries—comprising up to 80% of healthcare information (Chen et al., 2020). It enables extraction of relevant data points, improves predictive modeling, and automates administrative tasks like documentation and coding, which reduces clinician workload and enhances workflow efficiency. Natural Language Generation (NLG), a subset of NLP, is increasingly used for generating patient summaries, clinical reports, and tailored health communications, further advancing the usability of complex healthcare data (Croxford et al., 2025). NLP and ML algorithms are being integrated into real-time feedback systems, offering dynamic performance assessment and personalized coaching to accelerate competency development (Wartman & Combs, 2018). These innovations not only optimize the training pipeline but also ensure that clinical education keeps pace with the rapidly evolving demands of modern healthcare.

Future Potential: Future NLP applications will include automated summarization of vast amounts of medical literature to assist clinicians and researchers, improved and more sophisticated medical conversational agents that can provide personalized health information and support, automated generation of clinical documentation, and the ability to analyze patient narratives and feedback to gain insights into their experiences and preferences.

Quantitative Data: According to Cogent Infotech (2025), the adoption of NLP solutions in the healthcare and life sciences market is expected to increase from USD 2.2 billion in 2022 to USD 7.2 billion by 2027 at a CAGR of 27.1%. The contributors to this market growth include the increasing demand for predictive analytics to address significant health issues, the need to make electronic health record (EHR) data more usable, and the necessity to analyze and extract insights from narrative text. The socio-economic impact includes improved efficiency in processing clinical documentation, enhanced access to medical information, and potentially improved patient engagement through natural language interfaces.

Open Challenges: Challenges include the complexity and variability of medical language, the presence of jargon, abbreviations, and inconsistencies in clinical notes, ensuring the accuracy and reliability of information extracted by NLP systems, addressing privacy concerns when processing sensitive patient narratives, and the need for domain expertise to train and validate NLP models for healthcare applications (Meskó & Topol, 2023). Over-dependence on these tools could potentially hinder the development of fundamental clinical skills and the ability to reason through complex cases autonomously (García-Torres et al., 2024).

3.3. Devices & Wearables

This category includes physical devices used by patients and healthcare providers, often with connectivity features to collect and transmit data.

3.3.1. Wearable Devices

Wearable devices are electronic technologies worn on the body that collect and transmit data about the user's health and activity. These range from fitness trackers and smartwatches to more sophisticated medical-grade sensors.

Current Applications: Currently, wearable devices are widely used for tracking physical activity levels, monitoring heart rate, analyzing sleep patterns, and providing general wellness insights (Albites-Sanabria et al., 2024; Di Rienzo & Mukkamala, 2021; Lu et al., 2020). Some medical-grade wearables are used for

remote monitoring of specific conditions like atrial fibrillation or to support self-management of chronic conditions, e.g., for continuous glucose monitoring in diabetes management.

Future Potential: Future wearable devices will offer continuous and passive monitoring of a much wider range of physiological parameters, including blood pressure, oxygen saturation, hydration levels, and even early indicators of infectious diseases. They will be seamlessly integrated with healthcare platforms, providing real-time data streams that enable proactive health interventions and personalized feedback. Advanced wearables could also incorporate diagnostic capabilities.

Quantitative Data: The global wearable healthcare devices market size was valued at USD 39.9 billion in 2023 and is expected to reach USD 114.8 billion by 2033, according to a research report published by Spherical Insights & Consulting (2024). The socio-economic impact includes empowering individuals to monitor their health and make informed lifestyle choices, facilitating early detection of potential health issues, and supporting remote patient monitoring programs, potentially reducing the need for frequent clinic visits.

Open Challenges: Challenges include ensuring the accuracy and reliability of data collected by consumer-grade wearables, addressing data privacy and security concerns related to the continuous collection of sensitive personal health data, the need for regulatory frameworks for medical-grade wearables, ensuring usability and comfort for long-term wear, and integrating wearable data effectively into clinical workflows.

3.3.2. Connected Medical Devices

Connected medical devices are medical devices that are equipped with connectivity features, allowing them to transmit data to other devices, systems, or healthcare providers. This category overlaps with IoMT but focuses specifically on the medical devices themselves.

Current Applications: Current applications include connected glucose meters that transmit readings to a smartphone or cloud platform, smart blood pressure cuffs, connected infusion pumps that can be remotely monitored, and smart inhalers that track medication usage. These devices facilitate remote monitoring and improve data collection for both patients and clinicians.

Future Potential: Future connected medical devices will offer more advanced functionalities, including real-time adjustment of device settings based on patient data and AI analysis, predictive alerts for potential device malfunctions or patient deterioration, enhanced data sharing and interoperability between different devices and healthcare systems, and the development of closed-loop systems (e.g., automated insulin delivery systems).

Quantitative Data: Connected Healthcare Devices Market was valued at over USD 55 billion in 2023 and is estimated to register a CAGR of over 17.5% between 2024 and 2032, driven by the increasing demand for remote monitoring and data-driven healthcare (Global Market Insights, 2024b). The socio-economic impact includes improved management of chronic conditions, reduced hospitalizations and emergency room visits, and enhanced efficiency in data collection and analysis for healthcare providers.

Open Challenges: Key challenges include ensuring the cybersecurity of connected medical devices, which are vulnerable to hacking and data breaches, addressing regulatory complexities for connected devices, ensuring interoperability between devices from different manufacturers, managing the lifecycle and updates of connected devices, and establishing clear protocols for data ownership and access.

3.4. Advanced Technologies

This category encompasses emerging technologies with transformative potential across various sectors, including healthcare.

3.4.1. Blockchain

Blockchain is a decentralized, distributed ledger technology that records transactions across many computers. This makes the data immutable, transparent, and secure, as the network must validate any changes.

Current Applications: In healthcare, blockchain is being explored and piloted for securely storing and sharing patient data, managing supply chains for pharmaceuticals and medical devices to prevent counterfeiting, verifying the credentials of healthcare professionals, and facilitating secure and transparent clinical trial data management (Agbo et al., 2019; Engelhardt, 2017; Kuo et al., 2017).

Future Potential: The future of blockchain in healthcare could involve truly interoperable and patient-controlled health records, where individuals have ownership and control over who can access their data. It could revolutionize healthcare data marketplaces, enabling secure and transparent sharing of aggregated data for research while preserving patient privacy. Blockchain could also streamline claims processing and billing.

Quantitative Data: The blockchain in the healthcare market is still relatively nascent but is projected for significant growth as pilot projects demonstrate its value. The socio-economic impact could include enhanced data security and patient privacy, improved efficiency and transparency in healthcare operations, reduced fraud and errors in billing and supply chains, and accelerated medical research through secure data sharing.

Open Challenges: Challenges include the scalability of blockchain networks to handle the massive volume of healthcare data, the energy consumption of some blockchain protocols, regulatory uncertainty surrounding the use of blockchain in healthcare, the need for standardization and interoperability between different blockchain platforms, and the technical complexity of implementing and managing blockchain solutions (Haque et al., 2021; McGhin et al., 2019).

3.4.2. Augmented Reality (AR)

AR is a technology that overlays digital information, images, or models onto the real world, typically viewed through a device like a smartphone, tablet, or AR glasses.

Current Applications: In healthcare, AR is currently used for surgical planning and visualization, allowing surgeons to overlay patient imaging data onto the patient's body during procedures (Longo et al., 2024). It is also used in medical training and education, providing interactive anatomical models and simulations (Tang et al., 2020). AR can assist nurses in finding veins for injections.

Future Potential: Future AR applications in healthcare include image-guided surgery with real-time, highly accurate overlays of critical anatomical structures and patient data, immersive and interactive anatomy learning experiences for medical students, remote expert guidance for complex procedures where a remote surgeon can provide real-time visual instructions, and AR-based rehabilitation programs that provide interactive exercises and feedback.

Quantitative Data: AR in the healthcare market is a growing niche with increasing investment and development. The socio-economic impact includes improved surgical accuracy and outcomes, enhanced medical training and education, and potentially more engaging and effective rehabilitation programs.

Open Challenges: Challenges include the cost of AR hardware and software, the need for high-precision tracking and registration to ensure accurate overlays during procedures, developing user-friendly interfaces for medical professionals, addressing potential distractions or cognitive load caused by AR overlays, and regulatory approval for AR applications used in clinical settings.

3.4.3. Virtual Reality (VR)

VR is a technology that creates immersive, interactive simulated environments that users can experience through a VR headset.

Current Applications: VR is currently used in healthcare for medical training simulations, allowing trainees to practice procedures in a realistic and risk-free environment. It is also used for pain management and therapy, providing distracting and immersive experiences that can reduce the perception of pain (Alvarado-Omenat et al., 2025; Giannelli et al., 2024). VR is used in exposure therapy for treating phobias, anxiety, and post-traumatic stress disorders (PTSD) and for patient education (Donnelly et al., 2021).

Future Potential: Future VR applications will include highly realistic and haptic-feedback-enabled surgical training simulations, immersive rehabilitation programs that make exercises more engaging and effective, VR-based telemedicine consultations that provide a more immersive and personal interaction, and advanced VR environments for pain management and psychological therapies that are tailored to individual patient needs.

Quantitative Data: A comprehensive market research report by Grand View Research (2024b) estimates the global VR in healthcare market size at USD 5.62 billion in 2024, with a projected growth at a CAGR) of 30.3% from 2025 to 2030. The report highlights the increasing adoption of VR technologies in medical training, surgical simulation, patient care, rehabilitation, and therapy procedures. The growing demand for minimally invasive treatments and enhanced diagnostic tools has accelerated the use of virtual environments to improve procedural accuracy and patient outcomes. The socio-economic impact includes improved medical training outcomes, non-pharmacological approaches to pain management, and potentially more effective psychological therapies.

Open Challenges: Challenges include the cost of VR hardware and software, potential side effects like motion cybersickness, the need for content tailored to specific medical applications, ensuring the realism and accuracy of simulations for training purposes, and integrating VR therapy effectively into clinical workflows.

3.4.4. Robotics

Robotics in healthcare involves the use of robots to perform various tasks, ranging from surgical procedures to logistics and patient care assistance.

Current Applications: Surgical robots are widely used for minimally invasive procedures, offering increased precision, dexterity, and control for surgeons (Picozzi et al., 2024). Robots are also used for automated dispensing of medications in pharmacies, laboratory automation for handling samples and running tests, and for transporting materials and equipment within hospitals.

Future Potential: Future healthcare robotics will see the development of more advanced and autonomous surgical robots capable of performing increasingly complex procedures. Robots will play a larger role in direct patient care, assisting with tasks like lifting and transferring patients, providing physical therapy guidance, and even offering companionship. Automated logistics and inventory management within hospitals will become more sophisticated.

Quantitative Data: The global medical robotics market was valued at approximately USD 12.8 billion in 2024 and is projected to grow at a CAGR of 16.6% from 2025 to 2034 (Global Market Insights, 2024a). Key market segments are surgical robots, currently market lead, and rehabilitation robots, which are expected to be the fastest-growing segment. The socio-economic impact includes improved surgical outcomes, reduced recovery times for patients undergoing robotic surgery, increased efficiency in laboratory and pharmacy operations, and potentially reduced physical strain on healthcare workers.

Open Challenges: Challenges include the high cost of purchasing and maintaining medical robots, the need for specialized training for healthcare professionals to operate and interact with robots, addressing safety

concerns related to human-robot interaction in clinical settings, regulatory approval for new robotic applications, and the ethical considerations surrounding the increasing role of automation in patient care.

3.4.5. 3D Printing

3D printing, or additive manufacturing, is a process of creating three-dimensional solid objects from a digital model by adding material layer by layer.

Current Applications: In healthcare, 3D printing is currently used to create patient-specific prosthetics and implants that are customized for a perfect fit. It is also used to produce anatomical models from patient scan data for surgical planning and training. 3D printing is used to create customized medical devices and surgical guides (McAnena, McClennen & Zheng, 2025).

Future Potential: The future of 3D printing in healthcare includes the bioprinting of tissues and potentially even organs using living cells, revolutionizing transplantation and regenerative medicine. It will enable the on-demand printing of personalized medications with precise dosages and release profiles. 3D printing will also facilitate the creation of highly complex and customized medical devices and surgical tools at the point of care.

Quantitative Data: The global healthcare 3D printing market was valued at USD 8.52 billion in 2023 and is projected to reach USD 27.29 billion by 2030, growing at a CAGR of 18.5% from 2024 to 2030 (Grand View Research, 2023). The socio-economic impact includes the availability of highly customized medical devices and implants, potentially lower costs for certain medical products compared to traditional manufacturing, and accelerating research in regenerative medicine and drug development.

Open Challenges: Challenges include the regulatory approval process for 3D-printed medical devices and bio-printed tissues, ensuring the quality and safety of 3D-printed materials for medical use, the cost and accessibility of 3D printing technology in healthcare settings, the need for specialized skills to design and print medical products, and the ethical considerations surrounding bioprinting.

3.4.6. Digital Twins

A digital twin is a virtual replica of a physical object, process, or system that is continuously updated with real-time data from its physical counterpart. This allows for simulation, analysis, and optimization.

Current Applications: In healthcare, digital twins are being explored to create virtual replicas of organs or physiological systems to simulate disease progression and treatment responses (Viceconti et al., 2024). They are also used for optimizing hospital workflows, managing resources, and simulating the impact of changes to the healthcare system.

Future Potential: Future applications of digital twins in healthcare include creating patient-specific digital twins that integrate data from various sources (EHRs, wearables, genomics) to simulate the potential outcomes of different treatment options, enabling highly personalized medicine. Digital twins of hospitals and healthcare networks could optimize operations, predict bottlenecks, and improve disaster preparedness. They could also revolutionize clinical trial design by simulating patient responses.

Quantitative Data: The digital twin market in healthcare is still in its early stages but is expected to grow significantly as the technology matures and its benefits are demonstrated. The socio-economic impact could include more personalized and effective treatments, improved efficiency and cost savings in healthcare operations, and accelerated medical research and drug development through simulation.

Open Challenges: Challenges include the complexity of creating accurate and realistic digital twins of biological systems, the need for massive amounts of real-time data to keep digital twins updated, ensuring the interoperability of data sources, the computational resources required for running complex simulations, and

addressing data privacy and security concerns related to creating and using detailed digital replicas of individuals.

3.5. Advanced Computing

This category highlights the role of high-performance computing and the emerging field of quantum computing in addressing complex healthcare challenges.

3.5.1. High-Performance Computing (HPC)

HPC refers to the use of supercomputers and parallel processing techniques to solve complex computational problems that are too large or require too much time for standard computers.

Current Applications: In healthcare, HPC is currently essential for processing and analyzing large genomic datasets to identify genetic variations and understand disease mechanisms. It is used for molecular simulations in drug discovery and development to predict how potential drug candidates will interact with biological targets. HPC is also used for complex medical imaging processing and analysis (Li et al., 2024).

Future Potential: Future applications of HPC in healthcare will involve even more sophisticated genomic analysis for personalized medicine and disease prediction, accelerating the drug discovery and development process through large-scale simulations and virtual screening, enabling more advanced medical imaging analysis and reconstruction, and supporting large-scale epidemiological studies and public health modeling.

Quantitative Data: The use of HPC in healthcare and life sciences is a growing area driven by the increasing volume and complexity of biological and medical data. The socio-economic impact includes accelerating breakthroughs in genomics and personalized medicine, speeding up the development of new drugs and therapies, and improving our understanding of complex diseases.

Open Challenges: Challenges include the high cost of acquiring and maintaining HPC infrastructure, the need for specialized expertise to utilize HPC effectively for healthcare applications, managing and transferring large datasets to and from HPC systems, and ensuring the security and privacy of sensitive data processed on these platforms.

3.5.2. Quantum Computing

Quantum computing is a new paradigm of computing that uses the principles of quantum mechanics to perform calculations. Quantum computers have the potential to solve certain types of problems that are intractable for even the most powerful classical supercomputers.

Current Applications: Quantum computing in healthcare is currently in the research and development phase. Researchers are exploring its potential for drug discovery by simulating molecular interactions with unprecedented accuracy, optimizing complex treatment plans, and advancing medical imaging techniques (Flöther, 2023).

Future Potential: Future quantum computing applications in healthcare could revolutionize drug discovery by enabling the simulation of highly complex biological systems and the design of entirely new molecules. It could lead to the development of highly personalized treatment plans that account for an individual's unique genetic makeup and disease characteristics. Quantum computing could also enhance the capabilities of AI in healthcare by enabling more complex and powerful algorithms.

Quantitative Data: The quantum computing market in healthcare is currently very small, representing primarily research and development investments. However, it has the potential for significant future growth as the technology matures. The socio-economic impact is potentially revolutionary, leading to the discovery of new cures and therapies, highly personalized medicine, and unprecedented advancements in our understanding of biological systems.

Open Challenges: Significant challenges include the immaturity of quantum computing hardware and software, the difficulty in building and maintaining stable quantum systems, the need for specialized algorithms tailored for quantum computers, the high cost of quantum computing resources, and the need to train a workforce with the necessary skills in quantum mechanics and computer science.

3.6. Digital Therapeutics & Interventions

This category focuses on software-based interventions and programs designed to treat or manage medical conditions and support patient care.

3.6.1. Digital Therapeutics (DTx)

DTx are software programs that deliver evidence-based therapeutic interventions to prevent, manage, or treat a medical disorder or disease. Unlike general health and wellness apps, DTx are clinically validated, often prescribed by healthcare professionals, and are regulated as medical devices in many regions.

Current Applications: Current DTx applications include programs for managing chronic conditions like diabetes (e.g., providing behavioral support and glucose monitoring insights), treating mental health disorders such as anxiety and depression (e.g., delivering cognitive behavioral therapy), and managing substance abuse disorders (Chengyu, Xueyan & Ying, 2024; Fassbender et al., 2024).

Future Potential: Future DTx will be more integrated into clinical workflows, with seamless data exchange between the DTx program, patient, and healthcare provider. They will offer more personalized and adaptive therapeutic interventions based on real-time patient data and AI analysis. The range of medical conditions addressed by DTx is expected to expand significantly, including neurological disorders, cardiovascular diseases, and chronic pain.

Quantitative Data: Fortune Business Insights (2025b) projects the market of DTx to expand from USD 8.28 billion in 2024 to USD 43.88 billion by 2032, reflecting a CAGR of 23.2% during the forecast period, as regulatory frameworks mature and adoption increases. The socio-economic impact includes providing accessible and scalable therapeutic options, potentially reducing the need for traditional treatments and hospitalizations, and empowering patients to manage their conditions actively.

Open Challenges: Challenges include the need for rigorous clinical validation and regulatory approval for DTx products, establishing clear reimbursement pathways, ensuring equitable access to DTx for all patients, integrating DTx effectively into existing healthcare workflows, and addressing concerns about patient engagement and adherence to digital interventions.

3.6.2. Digital Care Programs

Digital care programs are comprehensive digital platforms and services designed to support patient care and management, often for specific conditions or patient populations. They can integrate various digital technologies to provide a holistic care experience.

Current Applications: Current digital care programs include remote patient monitoring programs for chronic diseases that integrate data from connected devices and provide educational content and support. They also include virtual rehabilitation programs, digital platforms for care coordination among multiple providers, and patient engagement platforms that provide personalized information and communication tools (Jansen et al., 2025).

Future Potential: Future digital care programs will represent highly integrated and personalized care pathways that leverage the full spectrum of digital technologies. They will be powered by AI for personalized care coordination, predictive risk assessment, and automated patient support. These programs will enable remote management of increasingly complex conditions and provide a more seamless and patient-centric healthcare experience.

Quantitative Data: The market for digital care programs is expanding as healthcare providers and payers seek innovative ways to manage patient populations and improve outcomes. The socio-economic impact includes improved care coordination, better management of chronic conditions, reduced healthcare costs through preventative care and reduced hospitalizations, and enhanced patient engagement and satisfaction.

Open Challenges: Challenges include ensuring the interoperability of different digital tools and platforms within a program, integrating digital care programs effectively into existing clinical workflows, addressing data privacy and security concerns when aggregating data from multiple sources, ensuring equitable access to these programs, and demonstrating their long-term effectiveness and cost-effectiveness.

4. The Transformative Impact of AI on Healthcare: Preempting Illness, System Management, and Community Care

Amid the 4th Industrial Revolution, science and technology are reshaping healthcare and patient management in truly remarkable ways. These advancements promise not only improved patient care but also cost savings through early diagnosis and treatment options. They address talent shortages, ensure secure and seamless access to patient data, and facilitate treatments in more comfortable outpatient settings. To capitalize on these medical breakthroughs, healthcare organizations must identify inefficiencies and be willing to experiment with novel technologies. It is crucial to include all stakeholders, especially patients, in this process to ensure their needs and inputs are considered. We are witnessing a dramatic transformation in patient care management thanks to innovations like hyper-personalized medicine, 24/7 support bots, and systems that proactively alert physicians to potential issues. Advancements in AI, nanotechnology, biosensors, and digital health monitoring have significantly enhanced the capability to predict, prevent, and preempt illnesses before they manifest. The shift from reactive to proactive medicine is being driven by technologies that enable continuous health monitoring, early diagnosis, and personalized treatment plans.

4.1 AI's Dependence on Health Data Collection, Availability, and Usability: the role of blockchain technologies

Data-driven strategies will likely dominate healthcare provider decision-making in the coming decade. The aggregation and application of data—encompassing patient information, IT infrastructure metrics, facility management data, and other diverse sources—will exert a significant influence on strategic discussions and organizational priorities. Similarly, the efficacy of AI in healthcare is contingent upon the availability of high-quality, comprehensive, and interoperable health data. AI models necessitate substantial datasets for training algorithms designed for disease prediction, treatment optimization, and patient risk stratification (Chen & Goldman, 2023). Nevertheless, challenges pertaining to data standardization, security protocols, and ethical governance persist.

The integration of blockchain technologies in healthcare is fundamentally altering the paradigms of medical data storage, sharing, and utilization. By providing a secure, decentralized, and immutable framework for managing electronic health records (EHRs), blockchain facilitates enhanced efficiency and streamlining of healthcare services. This technological advancement bolsters data reliability, interoperability, and security, resulting in improved patient care outcomes, cost reductions, and expanded access to outpatient services. As healthcare systems increasingly transition toward digital and cloud-based infrastructures, blockchain ensures data integrity, mitigates administrative inefficiencies, and strengthens the dynamics of patient-provider interactions (Agbo, Mahmoud& Eklund, 2019).

A salient contribution of blockchain technology in healthcare lies in its capacity to enable real-time, secure, and transparent data exchange among providers. Traditional EHR systems are often characterized by data silos, wherein information is stored in disparate and non-interoperable systems, thereby impeding healthcare professionals' access to a holistic view of a patient's medical history (Engelhardt, 2017). Blockchain

technology addresses this limitation by establishing a decentralized ledger that permits authorized stakeholders—including physicians, hospitals, laboratories, and insurers—to securely access and update records without compromising data integrity or patient privacy. Through cryptographic hashing and smart contracts, blockchain ensures that only authorized personnel can modify patient data, thereby minimizing errors, administrative delays, and redundancies in medical testing (Yue et al., 2016).

Another advantage of blockchain technology lies in its capacity to enhance the security and reliability of cloud-based healthcare services. With the increasing reliance on cloud storage for patient records, medical imaging, and genomic data, concerns regarding cybersecurity breaches, data manipulation, and unauthorized access have become increasingly salient (Zhang et al., 2018). Blockchain mitigates these risks through the encryption and decentralization of patient information, thereby precluding unilateral control over data by any single entity. This immutable ledger technology not only prevents fraudulent alterations but also fosters trust among healthcare providers and patients. Furthermore, blockchain-based solutions facilitate automated data reconciliation, enabling healthcare systems to maintain real-time, tamper-proof patient records, which significantly reduces medical errors and enhances the accuracy of diagnoses and treatment regimens (Kuo, Kim& Ohno-Machado, 2017).

From an economic standpoint, blockchain contributes to cost containment and enhanced operational efficiency within healthcare systems. Administrative processes, including insurance claims, billing procedures, and provider credentialing, are often characterized by complexity and protracted timelines. By leveraging blockchain-enabled smart contracts, healthcare organizations can automate these processes, thereby significantly reducing administrative overhead, eliminating fraudulent activities, and expediting insurance reimbursements (McGhin et al., 2019). This automation not only curtails operational expenditures but also enables healthcare professionals to allocate a greater proportion of their time to patient care rather than administrative tasks.

Blockchain further facilitates a transition towards outpatient and telemedicine services, thereby promoting a more cost-effective and accessible healthcare delivery model. Through secure and transparent data exchange mechanisms, providers can confidently offer remote consultations, AI-driven diagnostics, and personalized treatment plans while ensuring patient confidentiality (Roehrs et al., 2019). Patients with chronic conditions, mobility impairments, or those residing in remote geographic areas benefit from continuous, high-quality care without necessitating frequent in-person consultations. Blockchain-powered telemedicine platforms also ensure seamless coordination between specialists and general practitioners, thereby facilitating more efficient case management and improved health outcomes.

Moreover, blockchain technology facilitates advancements in precision medicine and genomic research by providing a secure and traceable framework for the sharing of genetic and biomedical data among researchers and healthcare institutions (Haque et al., 2021). Personalized medicine relies on the integration of patient-specific data, encompassing genomic sequencing, lifestyle factors, and medical history, to tailor individualized treatments. Through the application of blockchain, researchers can access large, anonymized datasets while upholding patient privacy and adhering to regulatory compliance standards, thereby accelerating the development of targeted therapies and more effective medical interventions (Zhang, Schmidt & White, 2020).

Despite its transformative potential, widespread adoption of blockchain in healthcare still faces regulatory and technological challenges. Issues such as scalability, standardization of protocols, and compliance with data protection laws (e.g., GDPR and HIPAA) must be addressed to fully realize its benefits (Esposito et al., 2018; Atella, Ganna & Lombardo, 2025, in this Special Issue). However, as governments, healthcare providers, and technology companies continue to invest in blockchain research and pilot projects, its integration into mainstream healthcare services is becoming increasingly viable.

In conclusion, blockchain technology presents a groundbreaking opportunity to enhance patient health through secure, efficient, and interoperable healthcare services. By providing reliable cloud-based infrastructures, enabling seamless record-sharing, reducing administrative costs, and expanding outpatient care options, blockchain is revolutionizing the way medical data is managed and healthcare is delivered. As the industry moves towards data-driven, patient-centric models, blockchain is poised to play an essential role in ensuring that healthcare systems remain resilient, cost-effective, and patient-focused.

4.2 How AI is pervading the world of incoming new technologies

AI is becoming an integral component of emerging technologies, shaping advancements across multiple domains, including healthcare, finance, transportation, and manufacturing. Its ability to process vast amounts of data, recognize patterns, and automate complex tasks has positioned it as a foundational element in the development of autonomous systems, predictive analytics, and human-machine collaboration (Russell & Norvig, 2021). In healthcare, AI enhances diagnostic accuracy, optimizes treatment plans, and streamlines administrative processes (Topol, 2019a,b; Brynjolfsson & McAfee, 2017). This is occurring in several new branches of medical innovation. Below, we describe some interesting breakthroughs.

Nanotechnology and Nanobots. Nanotechnology has emerged as a breakthrough field in medicine, offering solutions that range from targeted drug delivery to cellular repair and tissue regeneration. Nanobots, which are microscopic robotic systems, can be programmed to navigate through the bloodstream and detect biochemical markers associated with early-stage diseases such as cancer, cardiovascular disorders, and neurodegenerative conditions (Saini et al., 2021). Some researchers have developed nanobots coated with platelet and red blood cell membranes, enabling them to neutralize toxins and bacterial infections in the bloodstream more efficiently than traditional antibiotics (Han et al., 2022). Within this technology, AI facilitates targeted drug delivery, enabling nanobots to navigate the bloodstream and selectively attack malignant cells, improving cancer treatment while minimizing side effects (Santos et al., 2020). One of the most promising applications of nanomedicine is its ability to target malignant tumors at the cellular level. Unlike conventional chemotherapy, which affects both cancerous and healthy cells, nanobots can deliver highly localized treatments, reducing side effects and improving patient outcomes (Santos et al., 2020). Moreover, researchers have designed self-propelled nanobots that can travel through the cerebrospinal fluid, offering potential treatments for brain disorders and neurodegenerative diseases such as Alzheimer's and Parkinson's (Saniotis, et al., 2018; Krsek & Baticic, 2024).

Biosensors and Digital Tattoos. Biosensors represent another revolutionary advancement in preventive medicine. These wearable and implantable devices allow for continuous monitoring of vital physiological parameters, alerting patients and physicians in real time about potential health risks. Biosensors integrated into smartwatches, patches, and digital tattoos are capable of detecting blood glucose levels, cardiac rhythms, hydration status, and oxygen saturation (Lopez & Sun, 2022; Trung & Lee, 2016). Biosensors and digital tattoos powered by AI provide continuous health monitoring, detecting early signs of chronic conditions and optimizing disease management through real-time data analysis. A breakthrough in biosensor technology has been the development of graphene-based wearable sensors, which can detect specific cancer biomarkers through sweat analysis. Recent research has shown promising developments in non-invasive detection methods for early-stage gastric cancer. For instance, a study introduced an integrated AI-enabled system using One Class Twin Cross Learning (OCT-X) for early gastric cancer detection, achieving a diagnostic accuracy of 99.70% (Tang et al., 2024). Another research utilized deep learning on non-contrast CT scans, achieving a sensitivity of 85.0% and specificity of 92.6% for detecting gastric tumors (Liu et al., 2023). AI-powered predictive analytics further enhances the effectiveness of biosensors by processing vast datasets to detect patterns that indicate pre-disease conditions. For example, AI algorithms used in continuous glucose monitoring (CGM) devices can predict hypoglycemic events in diabetic patients up to three hours before they occur, allowing for timely intervention and improved glucose control (Sharma et al., 2022).

Haptic Technology and Robotic Surgery. AI-powered robotic surgical systems have enhanced precision, minimized invasiveness, and shortened recovery times. One of the most widely adopted technologies is the Da Vinci Surgical System, which allows robot-assisted laparoscopic procedures, reducing surgical complications and hospital stays (Liu, Wu et al., 2024). Recent advancements in haptic feedback technology enable surgeons to perform remote surgeries with an enhanced sense of touch, even when operating at a distance. Researchers have developed haptic glove systems that provide real-time force feedback, improving tactile sensitivity in robotic-assisted surgeries. This innovation has the potential to expand surgical expertise to remote and underserved regions, addressing global disparities in healthcare access. AI-driven haptic technology and robotic surgery improve surgical precision and enable remote procedures, expanding access to specialized care and reducing post-operative complications (Liu, Wu et al., 2024; Tozsin et al., 2024).

AI in Mental Health and Virtual Assistants. In mental health, AI-powered virtual assistants support cognitive behavioral therapy and provide real-time psychological assessments, increasing accessibility to mental health services and alleviating pressure on healthcare professionals. AI-powered chatbots and virtual mental health assistants are now widely used in telepsychiatry and cognitive behavioral therapy (CBT) (Vaidyam et al., 2019). AI-driven platforms such as Woebot and Wysa provide psychological support, monitor mental health trends, and offer personalized cognitive therapy exercises (Fulmer et al., 2018; Inkster et al., 2018). Studies show that these digital interventions can reduce symptoms of depression and anxiety while reducing the burden on human mental health professionals (Ravindran et al., 2021).

AI in Drug Development and Clinical Trial Optimization. Artificial Intelligence (AI) is transforming drug discovery and the evaluation of pharmaceutical safety by significantly enhancing the ability to simulate and predict drug interactions. Traditional drug development relies on time-intensive and costly clinical trials, often requiring six to eight years of testing and investments reaching hundreds of millions or even billions of dollars (Mak & Pichika, 2019). Moreover, nearly 80% of clinical trials fail to meet their enrollment targets, delaying the approval of new treatments and increasing financial risks (Huang et al., 2020). AI-driven approaches are now streamlining drug development, reducing the reliance on experimental assumptions, and expediting the research process while improving cost efficiency (Liu, Lu et al., 2024).

A notable example of AI's impact on pharmaceutical research is Decagon, an AI-based system developed by Stanford researchers to analyze protein-drug interactions. This system evaluates how approximately 5,000 existing pharmaceuticals interact with proteins in the human body, allowing researchers to identify potential side effects and adverse reactions with far greater speed and accuracy than traditional methods (Zitnik et al., 2018). By leveraging deep learning algorithms and vast biological datasets, AI tools such as Decagon offer a safer and more efficient alternative to animal testing and human trials, minimizing ethical concerns while improving predictive capabilities.

Beyond its applications in drug safety and efficacy analysis, AI is also revolutionizing patient recruitment for clinical trials. One of the most persistent challenges in clinical research is identifying and enrolling suitable participants, a process that is often hampered by inefficiencies in patient screening and eligibility matching. AI-driven systems are now being utilized to analyze electronic health records (EHRs) and genomic data, ensuring that patients who meet the specific criteria for a trial are identified in a timely manner (Topol, 2019a,b). By automating this process, AI enhances trial efficiency, increases patient participation, and ensures that individuals are matched to studies from which they are most likely to benefit.

The application of AI in drug research and clinical trial management marks a significant shift toward data-driven, precision medicine. By accelerating drug discovery, enhancing patient safety, and optimizing clinical trial workflows, AI is paving the way for a more efficient, cost-effective, and patient-centered pharmaceutical industry. As AI models continue to evolve, their role in drug repurposing, personalized treatment strategies, and the early identification of adverse drug reactions will become increasingly integral to the future of medical research.

4.3 AI's Role in Facilitating the Transition from Inpatient to Outpatient Care

AI is playing an increasingly pivotal role in transforming healthcare delivery by facilitating the transition of patients from inpatient to outpatient settings. As healthcare systems strive to enhance efficiency, reduce costs, and improve patient outcomes, AI-driven technologies are being leveraged to optimize post-discharge monitoring, personalized treatment plans, and remote patient management. These advancements support continuity of care, minimize hospital readmissions, and enable a more sustainable healthcare model focused on preventive and community-based care (Davenport & Kalakota, 2019).

One of the key areas where AI is making a substantial impact is in predictive analytics and early warning systems. AI algorithms analyze vast amounts of patient data to identify individuals at risk of complications, readmissions, or adverse events following hospital discharge. Machine learning models, trained on electronic health records (EHRs) and real-time physiological data, can detect subtle patterns indicative of deteriorating health, allowing clinicians to intervene proactively and prevent avoidable hospitalizations (Shameer et al., 2017). This predictive capability is particularly beneficial for managing patients with chronic diseases such as heart failure, chronic obstructive pulmonary disease (COPD), and diabetes, where continuous monitoring and timely interventions significantly reduce the likelihood of acute exacerbations (Kwon et al., 2020).

AI-powered remote patient monitoring (RPM) systems are revolutionizing outpatient care by enabling real-time tracking of vital signs, medication adherence, and rehabilitation progress. Wearable biosensors, combined with AI-driven analytics, allow healthcare providers to monitor blood pressure, glucose levels, oxygen saturation, and cardiac function without requiring patients to remain in a hospital setting (Krittanawong et al., 2019). These devices facilitate the early detection of potential complications, prompting timely medical interventions that prevent rehospitalization and enhance patient well-being. Additionally, AI-based virtual nursing assistants and chatbots, such as those integrated into mobile health applications, provide patients with personalized health guidance, medication reminders, and symptom assessments, fostering greater self-management and reducing dependence on in-person clinical visits (Bini, 2018).

The implementation of AI-driven telemedicine platforms has further streamlined the transition from inpatient to outpatient care by ensuring continuous access to medical professionals. AI-enhanced virtual consultations enable specialists, general practitioners, and allied healthcare professionals to conduct follow-ups, adjust treatment plans, and address patient concerns remotely, reducing the need for unnecessary hospital visits (Anghel et al. 2025; Shaik et al., 2025). This approach has proven particularly valuable in rural and underserved areas where access to healthcare services is limited. Telehealth solutions integrated with NLP and computer vision can assess patient speech, facial expressions, and physiological cues during virtual visits, providing clinicians with additional insights into a patient's condition (Esteva et al., 2021).

AI also plays a crucial role in optimizing hospital discharge planning and care coordination. Machine learning models can predict the most appropriate discharge pathways based on patient-specific factors, ensuring a seamless transition to home-based or rehabilitation care (Sendak et al., 2020). AI-powered discharge management systems facilitate better communication between hospitals, primary care providers, and home healthcare teams, reducing delays in follow-up appointments and ensuring that patients receive the necessary post-discharge support. These systems enhance interdisciplinary collaboration by integrating automated alerts, shared medical records, and AI-driven decision-support tools, thereby reducing administrative burden and improving continuity of care.

From an economic standpoint, the integration of AI in the transition from inpatient to outpatient care has significant cost-saving potential. Prolonged hospital stays contribute substantially to healthcare expenditures, and reducing the length of hospitalization through AI-guided outpatient management strategies alleviates financial strain on both healthcare systems and patients. Studies indicate that AI-enhanced remote monitoring and telehealth programs reduce hospital readmission rates by up to 30%, underscoring the financial and clinical benefits of leveraging AI-driven interventions (Madrid-Cagigal et al., 2025).

Despite its transformative potential, the widespread adoption of AI in facilitating inpatient-to-outpatient transitions faces challenges related to data privacy, algorithmic bias, and technology accessibility (see Atella, Ganna & Lombardo, 2025, in this Special Issue). Ensuring that AI models are trained on diverse and representative datasets is essential to prevent disparities in care delivery, particularly for marginalized populations. Moreover, the successful implementation of AI-driven solutions requires investment in digital literacy, clinician training, and regulatory frameworks that prioritize patient safety, transparency, and ethical AI deployment (Morley, Machado et al., 2020).

As AI continues to advance, its role in reshaping healthcare delivery, enhancing outpatient care, and reducing unnecessary hospitalizations will become increasingly pronounced. By leveraging predictive analytics, remote monitoring, telemedicine, and AI-driven care coordination, healthcare systems can transition towards a more patient-centered, efficient, and cost-effective model, ultimately improving population health and quality of life.

4.4 AI's Role in Healthcare System Management and Human Resource Optimization

Beyond direct patient care, the integration of AI in healthcare system management and human resource optimization is reshaping the workforce dynamics, particularly in workforce allocation, hospital logistics, and administrative efficiency, requiring new competencies and skills while simultaneously posing significant challenges for policymakers and healthcare administrators. As AI technologies enhance efficiency, diagnostic accuracy, and operational workflows, the demand for AI-literate healthcare professionals is increasing. To ensure that healthcare systems remain adaptive, sustainable, and capable of leveraging AI's full potential, decision-makers must proactively plan for workforce transformation, invest in skill development, and design policies that support AI integration while maintaining high standards of patient care (Jiang et al., 2017).

AI-powered solutions are streamlining clinical decision-making, predictive analytics, and automated administrative processes, reducing the burden of routine tasks on healthcare professionals. In diagnostics, AI algorithms are demonstrating remarkable accuracy in medical imaging, detecting anomalies in radiology, dermatology, and pathology with sensitivity levels comparable to or exceeding human specialists (Topol, 2019a,b). The ability of AI-driven systems to process vast amounts of clinical data in real-time is enhancing early disease detection, risk stratification, and personalized treatment planning (Rajpurkar et al., 2018). This transformation necessitates that clinicians, nurses, and allied health professionals develop competencies in AI interpretation, data analysis, and digital literacy to ensure that AI-powered recommendations are effectively integrated into clinical workflows (Paranjape et al., 2019).

Beyond clinical applications, AI is significantly improving hospital resource management, workforce allocation, and operational efficiency. AI-driven predictive staffing models are optimizing workforce distribution, ensuring that hospitals allocate human resources efficiently based on patient flow trends and demand forecasts (Davenport & Kalakota, 2019). In emergency departments, machine learning algorithms analyze historical admission patterns to anticipate patient influxes, allowing administrators to allocate personnel and resources proactively (El Ariss et al., 2024; Vural et al., 2025). AI-powered scheduling systems are reducing physician burnout by balancing workloads and automating shift assignments, creating more equitable work environments while preserving staff well-being (Uhde et al., 2020; Choudhry, 2022).

One of the most profound shifts driven by AI is in medical education and training. The traditional methods of training healthcare professionals are evolving to accommodate AI-based simulations, augmented reality (AR), and virtual reality (VR) applications, which provide interactive and immersive learning experiences (Tang et al., 2020). AI-powered simulated patient cases allow medical trainees to practice complex clinical decision-making scenarios, refining their diagnostic skills and procedural competencies in a risk-free environment (Tang et al., 2017). As AI continues to influence medical curricula, interdisciplinary education

that integrates healthcare, computer science, and bioinformatics is becoming essential for future healthcare professionals (Tozsin et al., 2024).

In workforce planning, AI is also playing a key role in credentialing, recruitment, and professional development. AI-driven platforms analyze candidate profiles, clinical expertise, and historical performance data to match healthcare professionals with positions that align with their skills and career trajectories (Nguyen et al., 2021). Additionally, AI-powered learning management systems track individual competency development, offering personalized training pathways and upskilling opportunities based on evolving healthcare demands. This shift underscores the need for healthcare institutions to foster lifelong learning environments where practitioners can continuously refine their expertise in alignment with technological advancements (Meskó et al., 2018).

The integration of AI in healthcare management is also prompting new ethical, legal, and regulatory considerations. Policymakers must establish guidelines for AI-driven decision support systems, ensuring that clinical accountability, data security, and patient safety remain paramount. Ethical concerns regarding AI bias, algorithmic transparency, and equitable access to AI-driven care necessitate ongoing regulatory oversight and governance frameworks (Morley, Machado et al., 2020). Additionally, healthcare leaders must navigate the transition to AI-augmented care models by fostering interdisciplinary collaboration between healthcare professionals, AI developers, and policymakers to create systems that enhance, rather than replace, human expertise (Char et al., 2020).

Preparing for this AI-driven transformation requires a multifaceted policy approach. Healthcare decision-makers must invest in workforce reskilling programs, AI-centric education, and organizational change management strategies to mitigate resistance and promote AI adoption. Strengthening public-private partnerships between academic institutions, healthcare providers, and technology firms can facilitate AI innovation, research, and skill development at scale. Governments and regulatory bodies must also adapt healthcare reimbursement models to recognize AI-assisted medical procedures and digital health interventions, ensuring that these technologies are sustainably integrated into routine care (Jiang et al., 2021).

As AI continues to redefine the healthcare landscape, the role of human expertise remains indispensable. The successful adoption of AI in healthcare hinges not only on technological progress but also on strategic workforce planning, comprehensive policy frameworks, and a culture of continuous learning. By aligning AI capabilities with healthcare workforce development, decision-makers can ensure that AI serves as an enabler of efficiency, accuracy, and accessibility rather than a disruptive force, ultimately improving patient outcomes and system-wide resilience.

AI is revolutionizing disease prevention, healthcare system efficiency, and community-based care models. From nanobots and biosensors to robotic surgery and telemedicine, AI-powered solutions are reshaping patient care, workforce management, and cost efficiency. However, the success of these technologies depends on ethical governance, data standardization, and equitable access. As AI continues to evolve, it has the potential to transform healthcare into a predictive, preventive, and patient-centric system. As AI continues to evolve, its ethical, regulatory, and socio-economic implications require careful consideration to ensure responsible and beneficial deployment (Floridi et al., 2018).

5. Application Areas: Transforming Healthcare Delivery and Patient Experience.

5.1 Telemedicine: Expanding Access to Care and Remote Monitoring.

Telemedicine utilizes telecommunications and information technology to provide clinical healthcare from a distance, and it emerged as an essential tool during the COVID-19 pandemic (Omboni et al., 2022). New technologies are significantly expanding the capabilities and reach of telemedicine, whose use is comparable

to in-person care across a variety of outcomes and clinical areas (Ezeamii et al., 2024). LLMs can enhance doctor-patient interactions during virtual consultations, offering real-time translation and summarizing key information. AI-powered remote patient monitoring systems, often integrated with wearable devices, allow for continuous tracking of physiological data, enabling early detection of health issues and personalized interventions. VR and AR can further augment telemedicine by enabling doctors to conduct sensory tests on patients with motor impairments during virtual visits and by projecting medical images onto a patient's body during video consultations, enhancing visual communication and remote diagnosis. Predictive analytics can identify patients who would benefit most from remote monitoring and predict potential health risks, allowing for proactive care delivery. HPC and big data infrastructure support the large-scale data transmission and analysis required for effective remote monitoring and telehealth services, ensuring secure and timely communication. Robotics also plays a role, with the development of telerobotics enabling remote surgeries and consultations, potentially increasing access to specialized treatments in underserved areas (Evans, Medina & Dwyer, 2018).

Telemedicine, empowered by these technologies, directly impacts the social dimension of the biopsychosocial model by breaking down geographical barriers and increasing access to healthcare services, especially for individuals in remote or underserved communities. Remote monitoring can also improve psychological well-being by providing patients with a sense of security and continuous support while also enabling early intervention for biological issues (Tan et al., 2024). Furthermore, telemedicine can enhance activity and participation for individuals with mobility limitations by allowing them to receive care and monitoring from the comfort of their homes. Commercial solutions in this area include platforms like Teladoc Health and Amwell, which offer virtual consultations, and companies like Biofourmis and Current Health (acquired by Best Buy Health), which provide AI-powered remote monitoring solutions.

5.2 Self-Assessment and Self-Management Tools: Empowering Patient Agency.

New technologies are providing patients with increasingly sophisticated tools for self-assessment and self-management of their health (Deniz-Garcia et al., 2023; Fassbender et al., 2024). LLMs can power chatbots that answer patient questions about symptoms, medications, and health conditions, improving health literacy and empowering individuals to take a more active role in their care. AI-driven mobile apps can analyze user-inputted symptoms and provide preliminary assessments, guiding individuals on when to seek professional help. VR and AR applications can educate patients about their conditions and treatment plans through immersive and interactive experiences, improving understanding and adherence. Predictive analytics can identify individuals at high risk for certain conditions, prompting them to adopt preventive behaviors and engage in self-management strategies. Wearable devices, integrated with big data analytics platforms, continuously collect health data, providing individuals with personalized insights and feedback to support self-management of chronic conditions like diabetes and hypertension.

These tools primarily impact the psychological dimension by increasing patients' knowledge, confidence, and sense of control over their health. Improved health literacy, facilitated by LLM-powered explanations and VR/AR-based education, can reduce anxiety and empower patients to make informed decisions about their care. By providing tools for remote monitoring and self-tracking, technology can also enhance activity and participation by enabling individuals to manage their conditions while maintaining their daily routines. Commercial examples include health and wellness apps like MyFitnessPal and Headspace, AI-powered symptom checkers like Ada Health, and wearable devices from companies like Fitbit and Apple.

5.3 Preventive Medicine: Utilizing Technology for Early Detection and Risk Reduction.

Technology is playing an increasingly vital role in preventive medicine, enabling early detection of diseases and reduction of health risks. AI algorithms can analyze vast datasets, including medical images, genetic

information, and lifestyle factors, to identify individuals at high risk for developing certain conditions like cancer, diabetes, and cardiovascular diseases, allowing for timely interventions (Hao et al., 2024). Predictive analytics models can forecast disease outbreaks and identify populations at risk, enabling public health organizations to implement targeted prevention strategies (Golinelli et al., 2025). Digital biomarkers, derived from data collected through wearable sensors and other digital health tools, can provide continuous monitoring of physiological parameters, detecting subtle changes that may indicate early stages of disease (Jabara et al., 2024). Quantum computing holds future potential for accelerating the analysis of complex biological data to identify novel biomarkers for early disease detection.

Preventive medicine strategies leveraging these technologies primarily impact the biological dimension by enabling early detection and intervention, potentially preventing or delaying the onset of chronic diseases. By providing individuals with risk assessments and personalized recommendations, technology can also influence psychological well-being by empowering them to make proactive lifestyle changes. Public health initiatives informed by predictive analytics and digital surveillance systems can improve the overall health of communities, addressing the social determinants of health and promoting health equity. Commercial solutions include AI-powered diagnostic tools for medical imaging from companies like Enlitic and Viz.ai, as well as predictive analytics platforms for healthcare organizations from companies like Optum and Cerner (now Oracle Health).

5.4 Clinical Decision Support Systems: Enhancing Diagnostic Accuracy and Treatment Guidance.

Clinical Decision Support Systems (CDSS) utilize new technologies to assist healthcare professionals in making more informed and accurate decisions regarding vaccination, diagnosis and treatment (Grechuta et al., 2024; Specchia et al., 2024). LLMs can analyze patient records and medical literature to provide clinicians with relevant information, diagnostic suggestions, and treatment options, enhancing their decision-making capabilities. AI algorithms can analyze medical images, laboratory results, and patient data to identify patterns and anomalies that may be missed by human review, improving diagnostic accuracy and speed. NLP can extract key information from unstructured clinical notes and present it in a structured format, making it easier for clinicians to review patient histories and identify relevant factors for decision-making. Predictive analytics can forecast patient outcomes and treatment responses, helping clinicians choose the most effective interventions for individual patients.

CDSS primarily impact the biological dimension by improving the accuracy and efficiency of diagnoses and treatment plans, leading to better patient outcomes. By providing clinicians with comprehensive and timely information, CDSS can also reduce stress and improve their confidence in making critical decisions, indirectly benefiting their psychological well-being. Furthermore, by standardizing care pathways and reducing diagnostic errors, CDSS can contribute to more equitable healthcare delivery, impacting the social dimension. Commercial examples include IBM Watson Health, Epic's integrated decision support tools, and numerous AI-powered diagnostic platforms for various specialties.

5.5 Point-of-Care (PoC) Diagnostics: Enabling Rapid and Convenient Testing.

Point-of-Care (PoC) diagnostics involve medical testing performed near or at the site of patient care rather than in a centralized laboratory. New technologies are enhancing the speed, accuracy, and accessibility of PoC diagnostics. AI algorithms can be integrated into portable diagnostic devices to analyze results in real-time, providing immediate feedback to healthcare providers (Pillay, Khan & Yenice, 2025). Digital biomarkers, collected through wearable sensors and analyzed using AI, can function as continuous PoC diagnostics, monitoring patient health status outside of traditional clinical settings. Microfluidics and nanotechnology are enabling the development of miniaturized and highly sensitive PoC testing devices for a wide range of analytes. Telemedicine platforms can facilitate specialists' remote interpretation of PoC test results, expanding access to diagnostic expertise.

PoC diagnostics primarily impact the biological dimension by enabling rapid and convenient testing, leading to quicker diagnoses and faster initiation of treatment. The accessibility of PoC testing can also improve psychological well-being by reducing anxiety associated with waiting for lab results and by allowing for immediate clinical decisions. Furthermore, by bringing diagnostic capabilities to the patient's location, PoC diagnostics can significantly improve access to healthcare for individuals in remote areas or with limited mobility, addressing the social dimension of health. Commercial examples include rapid antigen tests for infectious diseases, portable blood glucose monitors, and handheld ultrasound devices.

5.6 Digital Biomarkers: Continuous Health Monitoring and Personalized Insights.

Digital biomarkers are defined as physiological and behavioral data that are collected and measured by digital devices, such as wearables, portables, implantables, or digitals, and are used to explain, influence, and/or predict health-related outcomes (Goldhahn, 2017; Rochester et al., 2020). New technologies are crucial for the development and application of digital biomarkers. AI and machine learning algorithms are essential for analyzing the large volumes of data generated by these devices to identify meaningful patterns and insights. Wearable sensors can continuously monitor a wide range of physiological parameters, including heart rate, activity levels, sleep patterns, and glucose levels. NLP can be used to analyze patient-generated text data from journals or social media to identify behavioral biomarkers related to mental health or disease progression. Predictive analytics can leverage digital biomarker data to forecast health risks and predict disease exacerbations, enabling proactive interventions(Albites-Sanabria et al., 2024).

Digital biomarkers provide continuous insights into a patient's biological state, allowing for personalized monitoring and early detection of health changes. The Mobilise-D consortium, for example, has developed and validated digital mobility outcomes (DMOs) for remotely monitoring physical mobility, which can be crucial for managing various health conditions (Rochester et al., 2020). The ability to track and understand their health data can also improve patients' psychological well-being by increasing their awareness and motivation to engage in healthy behaviors. Remote monitoring through digital biomarkers can enhance social health by allowing individuals to manage their conditions from home and maintain their independence. Activity and participation can be directly measured and encouraged through wearable devices that track movement and provide feedback. Commercial examples include wearable devices like the Apple Watch and Fitbit, continuous glucose monitoring systems from Dexcom and Abbott, and various AI-powered platforms for analyzing digital biomarker data.

5.7 In Silico Medicine: a Critical Enabler of Precision Medicine.

In Silico Medicine (ISM) represents a transformative approach in healthcare, where sophisticated computational models simulate biological processes at organ, tissue, and even cellular levels. Closely related to the concept of digital twins, ISM differs in scope: while digital twins are dynamic, continuously updated virtual replicas of specific patients or systems, ISM provides the scientific and technological foundation for their creation, validation, and use in predictive, personalized, and preventive medicine (Katsoulakis et al., 2024; Viceconti et al., 2024). Regulatory agencies like the FDA and EMA are increasingly recognizing ISM-based evidence in regulatory decisions, especially for medical devices and pharmacological modeling.

The development and deployment of ISM rely heavily on a convergence of advanced technologies. Artificial Intelligence (AI) and machine learning algorithms enable the construction and calibration of complex models capable of simulating physiology and forecasting treatment outcomes. Big data analytics is essential for integrating diverse data sources, including electronic health records (EHRs), medical imaging, genomics, and wearable sensors, into computational frameworks (Viceconti et al., 2024). These simulations often require high-performance computing (HPC) infrastructure to perform real-time, multiscale analyses, while virtual reality (VR) and augmented reality (AR) platforms enhance user interaction with the models, supporting decision-making and communication between clinicians and patients.

ISM has the potential to profoundly influence healthcare by supporting individualized treatment planning, testing interventions virtually before implementation, and improving outcomes through enhanced physiological insight. Moreover, immersive visualization of complex data can reduce patient anxiety and improve clinician confidence, contributing to psychological well-being (Katsoulakis et al., 2024).

Pioneering research in ISM is being conducted at several leading institutions. The Insigneo Institute at the University of Sheffield is a global reference in the modeling of musculoskeletal systems and predictive simulations. The Auckland Bioengineering Institute in New Zealand excels in integrated modeling of organ-level physiology, while Johns Hopkins University's Computational Cardiology Lab has made major advances in in silico simulation of cardiac function and electrophysiology.

Commercial applications are also emerging. For instance, Atlas Meditech has developed tools that allow brain surgeons to rehearse operations using AI-enhanced 3D platforms and VR environments. Their systems generate realistic, patient-specific brain models based on CT and MRI data, enabling precise surgical planning and training.

However, the widespread adoption of ISM and related technologies is currently limited by high implementation costs. Establishing these platforms requires investment in a wide range of enabling technologies—including smart automation, CAD, product lifecycle management (PLM), model-based systems engineering (MBSE), and extended reality (XR)—as well as the IT infrastructure to support real-time processing and secure data integration. While these costs are substantial, they are increasingly seen as a necessary investment for advancing precision medicine and clinical innovation.

5.8 Digital Therapeutics: Delivering Software-Based Interventions for Various Conditions.

Digital therapeutics (DTx) are evidence-based software programs designed to prevent, manage, or treat a medical disease or disorder (Chengyu, Xueyan & Ying, 2024; Fassbender et al., 2024). New technologies are central to the development and delivery of DTx. AI algorithms can personalize treatment plans and adapt interventions based on individual patient progress and data. Mobile apps and web-based platforms provide convenient and accessible delivery mechanisms for DTx. VR and AR can enhance the engagement and effectiveness of DTx by creating immersive therapeutic experiences for conditions like phobias, PTSD, and chronic pain. Digital biomarkers, collected through wearable devices, can provide objective measures of treatment adherence and outcomes for DTx.

Digital therapeutics can directly address psychological health by providing accessible and personalized interventions for mental health conditions like anxiety, depression, and insomnia. They can also impact biological health by supporting the management of chronic conditions such as diabetes, hypertension, and obesity through lifestyle modifications and behavioral changes. By providing remote access to therapy and support, DTx can improve social health by reducing barriers to care and increasing patient engagement. Activity and participation can be promoted through DTx that incorporate gamification and tracking of physical activity. Commercial examples include FDA-approved DTx like Pear Therapeutics' reSET for substance use disorder and Somryst for chronic insomnia, as well as numerous other DTx in development for a wide range of conditions.

5.9 Pain Management: Innovative Technological Solutions for Chronic and Acute Pain.

New technologies are offering innovative solutions for managing both chronic and acute pain (Tan et al., 2024). VR therapy has shown promise in reducing pain perception by distracting patients and creating immersive experiences that can alter pain pathways in the brain (Giannelli et al., 2024). AR can be used to overlay information and guidance during physical therapy exercises for pain rehabilitation. Digital therapeutics can deliver cognitive behavioral therapy and other psychological interventions for chronic pain

management through mobile apps and web-based platforms. Wearable devices can provide neuromodulation or electrical stimulation to alleviate pain. AI algorithms can analyze patient data to personalize pain management plans and predict treatment responses.

These technologies primarily impact the biological dimension by providing non-pharmacological approaches to pain relief and management. VR and digital therapeutics can also significantly improve psychological well-being by reducing the emotional distress and anxiety associated with chronic pain. By enabling more effective pain management, technology can enhance activity and participation by allowing individuals to engage more fully in their daily lives. Commercial examples include VR pain management programs from companies like AppliedVR and Firsthand Technology and wearable pain relief devices from companies like NeuroMetrix and TENS units.

5.10 Health Literacy: Leveraging Technology to Improve Patient Understanding.

Technology plays a crucial role in enhancing health literacy, which is the degree to which individuals have the capacity to obtain, process, and understand basic health information and services needed to make appropriate health decisions (Deniz-Garcia et al., 2023; Pierce at al., 2025). LLMs can generate patient education materials in plain language, answer patient questions in an accessible manner, and translate complex medical information into various languages. VR and AR can provide immersive and interactive educational experiences, allowing patients to visualize their conditions and treatment plans in a way that is easier to understand than traditional text-based materials. Multimedia resources, including videos and animations, delivered through digital platforms can cater to different learning styles and improve comprehension. AI-powered chatbots can provide personalized health information and guidance based on individual patient needs and questions.

Improving health literacy through technology primarily impacts the psychological dimension by increasing patients' understanding of their health conditions and treatment options, reducing anxiety, and empowering them to make informed decisions. Better understanding can also lead to increased adherence to treatment plans, positively impacting biological health. By making health information more accessible and understandable, technology can also improve social health by enabling individuals to navigate the healthcare system more effectively and advocate for their own needs. Commercial examples include patient education platforms like Krames and Healthwise, as well as various health information websites and apps.

5.11 Digital Consent: Streamlining and Securing the Informed Consent Process.

New technologies are transforming the process of obtaining informed consent from patients. Digital platforms can present consent forms in a clear and interactive manner, incorporating multimedia elements like videos and animations to explain procedures and risks more effectively than traditional paper-based forms (Cohen et al., 2023). LLMs can simplify the language of consent forms, making them easier for patients to understand. Electronic signatures and secure digital records streamline the consent process and ensure proper documentation. Telemedicine platforms with integrated digital consent features allow for remote consent, improving accessibility for patients in remote locations. Blockchain technology can provide a secure and auditable record of the consent process, enhancing trust and transparency.

Digital consent processes primarily impact the psychological dimension by improving patients' understanding of the information they are consenting to, leading to more informed decisions and potentially reducing anxiety. The streamlined and convenient nature of digital consent can also improve social health by making the process more accessible and less burdensome for patients. Secure digital records also contribute to the ethical and legal aspects of healthcare. Commercial solutions include electronic health record systems

with integrated e-consent functionalities from vendors like Epic and Cerner (now Oracle Health), as well as dedicated digital consent platforms like DocuSign and Formstack.

5.12 Digital Clinical Trials: Enhancing Efficiency and Accessibility in Research.

Technology is revolutionizing the design, conduct, and analysis of clinical trials. Digital platforms can facilitate remote patient recruitment and enrollment, expanding the reach and diversity of study participants. Wearable devices and mobile apps enable remote and real-world data collection outside traditional clinical settings, reducing the need for frequent in-person visits and improving patient convenience (Mittermaier, Venkatesh & Kvedar, 2023). AI and machine learning algorithms can assist in identifying suitable candidates for trials based on complex inclusion and exclusion criteria, speeding up the recruitment process. NLP can analyze unstructured data from patient records to identify potential trial participants and extract relevant information for analysis. Predictive analytics can forecast patient dropout rates and identify factors influencing trial outcomes. Digital platforms also enhance data management, monitoring, and communication between researchers and participants.

Digital clinical trials primarily impact the social dimension by increasing accessibility to research participation for a wider range of individuals, including those in remote areas or with mobility limitations. The convenience of remote participation and data collection can also improve the psychological well-being of participants. By accelerating the pace of research and improving the efficiency of trial processes, technology ultimately contributes to advancements in biological health through the development of new treatments and therapies. Commercial solutions include platforms like Medable and Science 37, which offer end-to-end solutions for conducting decentralized clinical trials.

5.13 Digital Surveillance Systems: Monitoring and Managing Public Health.

New technologies are crucial for enhancing public health surveillance and management. AI algorithms can analyze large datasets from various sources, including social media, news reports, and healthcare records, to detect and predict disease outbreaks in real-time. NLP can analyze text data for early signals of public health threats and monitor public sentiment and information related to health issues. Predictive analytics can forecast the spread of infectious diseases and identify high-risk populations, enabling timely public health interventions (Shakeri Hossein Abad et al., 2021). Geographic information systems (GIS) and mobile technologies can be used to track disease spread and coordinate response efforts.

Digital surveillance systems directly impact the biological dimension by enabling early detection and control of disease outbreaks, protecting public health. By providing timely and accurate information to the public, these systems can also improve psychological well-being by reducing anxiety and uncertainty during public health emergencies. Effective public health surveillance contributes to social well-being by ensuring the health and safety of communities. Commercial examples include platforms developed by public health agencies like the CDC and WHO, as well as private sector solutions for disease surveillance and outbreak prediction.

5.14 Virtual and Physical Assistants: Supporting Patients and Healthcare Professionals.

Technology is enabling the development of both virtual and physical assistants to support patients and healthcare professionals. Virtual assistants, often powered by AI and NLP, can answer patient questions, schedule appointments, provide medication reminders, and offer emotional support (Cuthbert et al., 2024). Physical assistants, such as soft wearable exoskeletons, can aid in rehabilitation, provide support for individuals with mobility impairments, and reduce the physical strain on healthcare workers (Abery, Canetti & Hing, 2025). Robots are also being used to automate logistical tasks within hospitals, such as transporting supplies and medications, freeing up nurses and other staff to focus on direct patient care.

Virtual assistants can improve psychological well-being by providing patients with readily available information and support, reducing feelings of isolation and anxiety. Physical assistants like exoskeletons can enhance biological health by improving mobility and reducing physical strain. By automating tasks and providing support, both virtual and physical assistants can improve social health by increasing efficiency and allowing healthcare professionals more time for direct patient interaction and personalized care. Activity and participation can be directly supported by physical assistants that aid mobility and rehabilitation. Commercial examples include AI-powered chatbots from various healthcare providers and technology companies, as well as wearable exoskeletons like the ones developed by ABLE Human Motion and ReWalk Robotics.

5.15 Age-Friendly Solutions: Tailoring Technology to the Needs of Older Adults.

Technology is playing an increasingly important role in creating age-friendly environments and healthcare solutions that cater to the specific needs and challenges faced by older adults (Sülz et al., 2021; Dogra et al., 2022). AI-powered virtual assistants can provide reminders for medications and appointments, offer companionship, and assist with daily tasks. Wearable sensors can monitor vital signs and activity levels, alerting caregivers or healthcare providers to potential health issues. Telemedicine platforms with user-friendly interfaces can facilitate remote consultations and monitoring, reducing the need for travel. VR and AR applications can provide engaging cognitive training and social interaction for older adults. Robotics, including social robots and assistive robots, can provide companionship, assist with mobility, and support daily living activities.

Age-friendly technologies can significantly improve the psychological well-being of older adults by reducing feelings of loneliness and isolation, providing cognitive stimulation, and increasing their sense of independence and control. By enabling remote monitoring and early detection of health issues, these solutions can also positively impact biological health. Improved access to care through telemedicine and assistance with daily living activities can enhance social health by allowing older adults to maintain their independence and social connections. Assistive robots and wearable devices can directly support activity and participation by improving mobility and enabling engagement in daily tasks. Commercial examples include social robots like Pepper and Paro, telehealth platforms designed for seniors, and various wearable health monitoring devices.

5.16 Innovative Health Data Representations: Visualizing Complex Information for Better Understanding.

New technologies are enabling innovative ways to represent complex health data, making it easier for both patients and healthcare professionals to understand and interpret (Cuthbert et al., 2024). Interactive dashboards and visualizations can present large datasets in a user-friendly format, allowing for easy identification of trends and patterns. VR and AR can transform traditional 2D medical images into interactive 3D models, providing a more intuitive understanding of anatomical structures and medical conditions. Digital twins offer a dynamic and personalized way to visualize an individual's health status and potential treatment outcomes. AI-powered platforms can generate summaries and highlight key insights from complex medical reports, making it easier for clinicians to grasp the most important information quickly (Croxford et al., 2025).

Innovative health data representations primarily impact the psychological dimension by improving understanding and reducing the cognitive burden associated with complex medical information for both patients and clinicians. Better visualization can lead to more informed decision-making and increased confidence in treatment plans, positively impacting biological health [10]. By making health data more accessible and understandable, technology can also improve social health by empowering patients to engage more actively in discussions about their care. Commercial examples include data visualization tools from

companies like Tableau and Qlik, as well as specialized medical imaging software and platforms for creating digital twins.

6. Maturity Assessment of Digital Health Solutions

As digital technologies increasingly permeate healthcare, the concept of maturity assessment has emerged as a critical tool for evaluating the current development stage, adoption feasibility, and systemic impact of digital health solutions. Assessing the maturity of these innovations is essential for understanding not only their technical robustness but also their readiness for integration into clinical workflows, health system governance, and public acceptance. This multidimensional evaluation framework allows policymakers, investors, and healthcare managers to prioritize interventions, allocate resources efficiently, and foresee potential regulatory or economic challenges.

Maturity in digital health can be dissected into at least three interrelated domains: technological readiness, innovation diffusion, and societal acceptance. Technological readiness refers to the level of technical development and performance reliability of a solution. This includes the solution's functionality, interoperability, and scalability. For instance, while some AI-based diagnostic tools have achieved high levels of technical maturity and clinical performance (Esteva et al., 2019), others remain experimental and lack validation across diverse population groups (Topol, 2019a,b).

Innovation readiness refers to the extent to which a digital health solution is integrated into clinical and administrative processes. A highly innovative product may still fail to gain traction if health institutions lack the infrastructure or capacity to adopt it effectively (Greenhalgh et al., 2017). Meanwhile, societal readiness involves public trust, ethical acceptability, and cultural alignment. Technologies such as telemedicine, though technically viable for over a decade, experienced delayed widespread adoption in part due to concerns about data privacy, patient-doctor interaction, and reimbursement policies—concerns that only began to shift substantially during the COVID-19 pandemic (Whitelaw et al., 2020).

Understanding these varying levels of maturity is not merely an academic exercise. It has profound implications for regulatory strategy and healthcare expenditure. Technologies at a low maturity stage may require regulatory sandboxes, pilot testing, or conditional approvals to balance innovation with safety. In contrast, highly mature solutions may warrant accelerated pathways and systemic integration incentives. Moreover, maturity assessment informs cost-effectiveness analyses, as immature technologies often entail high initial costs, uncertain returns, and organizational disruption (Huang et al., 2019). In contrast, mature technologies with proven clinical utility can drive long-term cost savings through better disease management, prevention, and operational efficiencies.

The European Commission has also underscored the importance of technology readiness assessment as a prerequisite for large-scale investment and public-private collaboration in health innovation (European Commission, 2020b). In the UK, the NHS has adopted digital maturity indices to evaluate the readiness of healthcare providers to integrate technologies and support decision-making in national funding allocations (NHS England, 2019).

Below and in Table 2 we report and discuss the maturity assessment of some key digital health applications:

- Technological Readiness Levels (TRL). This framework assesses the maturity of a technology based on a scale of 1 to 9, with 9 being the most mature (Mankins, 1995). Telemedicine is generally considered to be at TRL 9, as it is widely deployed and commercially available in many healthcare systems. mHealth apps for medication safety range from TRL 7 to 9, with various apps available to support clinical decisions and enhance medication use monitoring, although their effectiveness is still under investigation (Willemse et al., 2024) . VR for anxiety reduction is estimated at TRL 6 to 7, having demonstrated efficacy in research settings and gradually moving towards broader clinical adoption

(Donnelly et al., 2021). LLMs for virtual assistants are currently at TRL 5 to 7, showing promising results in research but still in the early stages of integration into clinical practice (Omar et al., 2024). Digital biomarkers, such as the DMOs being developed by the Mobilise-D consortium, are generally at TRL 4 to 6, indicating that they are under development and validation (Rochester et al., 2020).

- HealthTech Innovation Readiness (HIR). This level assesses the readiness of a health technology for adoption and scaling within healthcare systems, considering factors such as clinical validation, regulatory approval, and market viability (CIMIT, 2017). Telemedicine has a High HIR as it is well-integrated into many healthcare systems and has established reimbursement models. mHealth apps have a Medium to High HIR, with increasing adoption rates, but challenges remain regarding regulation and the need for robust evidence of their clinical impact. VR for anxiety reduction has a Low to Medium HIR, requiring further integration into clinical workflows and demonstration of cost-effectiveness to achieve widespread adoption. LLMs for virtual assistants currently have a Low to Medium HIR due to ongoing concerns around data privacy, accuracy, and the need for clear regulatory pathways. Digital biomarkers also have a Low to Medium HIR, facing challenges in standardization, validation, and seamless integration with existing clinical data systems.
- Societal Readiness Levels (SRL). This level reflects the societal acceptance, ethical implications, and regulatory frameworks surrounding a particular technology (Innovation Fund Denmark, 2015). Telemedicine has a High SRL, as it is generally accepted by both patients and healthcare providers, and regulatory frameworks are largely in place. mHealth apps have a Medium SRL, with some public concerns regarding data privacy, security, and the quality of health information provided. VR for anxiety reduction has a Medium SRL, with potential concerns related to accessibility, usability, and the immersive nature of the technology for some individuals. LLMs for virtual assistants currently have a Low to Medium SRL due to significant ethical considerations surrounding potential biases, the accuracy of information provided, and the potential for replacing human interaction in care; regulatory frameworks are still in the early stages of development. Digital biomarkers have a Medium SRL, with ongoing discussions around data ownership, privacy, and the appropriate interpretation of continuous data streams generated by these technologies.

Table 2: Maturity Assessment of Key Digital Health Applications

Application	Enabling Technology (ies)	TRL	HIR	SRL	Example/Source
Telemedicine	Digital technologies, IoT	9	High	High	Widely used for remote consultations.
mHealth apps for medication safety	Mobile health, AI	7-9	Medium-High	Medium	Apps providing medication reminders and information (Fang et al., 2023).
VR for anxiety reduction	VR	6-7	Low-Medium	Medium	Study showing reduced anxiety in cancer patients (Alvarado-Omenat et al., 2025) .
LLMs for virtual assistants	AI (LLMs, NLP)	5-7	Low-Medium	Low-Medium	Improved accuracy for complex health inquiries (Omar et al., 2024).

Digital mobility outcomes (DMOs)	Wearable sensors, AI	4-6	Low-Medium	Medium	Development by Mobilise-D consortium for remote monitoring (Rochester et al., 2020) .

In conclusion, assessing the maturity of digital health solutions is essential to aligning innovation trajectories with system-wide priorities and constraints. It enables a proactive, evidence-informed approach to health technology governance, ensuring that emerging solutions contribute meaningfully to clinical outcomes, system sustainability, and equitable access.

7. Potential Impacts: Transforming Healthcare Outcomes, the Organization, and the Healthcare Expenditure.

As seen in the previous sections, digital technologies are playing an increasingly transformative role in the healthcare sector, reshaping not only the quality of clinical outcomes but also the overall organization and the economic dynamics of health systems. As global healthcare systems contend with the mounting pressures of aging populations, rising chronic disease prevalence, and budgetary constraints, the adoption of digital innovations such as AI, telemedicine, remote monitoring, and integrated health platforms is enabling new models of care that are more personalized, efficient, and sustainable.

Table 3: Potential Impacts of New Technologies in Healthcare

Application Area	Impact Category	Specific Impact	Supporting Data/Examples
AI-powered diagnostics	Clinical Outcomes	Improved survival rates through early disease detection.	AI aiding in the interpretation of medical imaging.
Remote Patient Monitoring	Clinical Outcomes	Better management of chronic conditions, reduced hospital readmissions.	Continuous glucose monitoring for diabetes management.
VR for mental health	Clinical Outcomes	Reduction in anxiety and pain.	VR significantly decreased anxiety in cancer patients.
Decentralized Clinical Trials	Cost-Effectiveness	Lower costs and faster recruitment for clinical trials.	Digital platforms enabling remote participation.
Telemedicine	Social Benefits	Increased access to care for remote and underserved populations.	Telehealth improving patient access.
Digital Health Ecosystems	Workforce Shift	Emergence of new roles like telehealth coordinators and data analysts.	Integration of LLMs into VA platforms.
All Application Areas	Education/Reskilling	Need for training in using new technologies and interpreting digital data.	Healthcare professionals needing skills in telemedicine and AI-driven tools.

Table 3 summarizes some of the directions along which impacts are observed. Below, we discuss in more detail these impacts following the categories listed in Table 3.

Clinical Outcomes. From a clinical perspective, digital tools have significantly improved diagnostic accuracy, treatment personalization, and disease monitoring, leading to better health outcomes. AI algorithms are now capable of detecting conditions like diabetic retinopathy, breast cancer, and cardiac arrhythmias with levels of accuracy comparable to, or even exceeding, human specialists (Esteva et al., 2019;

Topol, 2019a,b). Similarly, digital biomarkers and wearable devices allow for continuous, real-time monitoring of patients with chronic conditions such as heart failure or diabetes, enabling earlier interventions and reducing emergency hospitalizations (Insel, 2017; Steinhubl et al., 2015). Digital health platforms also foster greater patient engagement and adherence by delivering tailored health information and facilitating two-way communication with care teams (Murray et al., 2011). AI-driven diagnostic tools can lead to earlier and more accurate diagnoses, which can dramatically increase survival rates for diseases like lung cancer, potentially improving the five-year survival rate from 10% to 70% (Huang, Yang et al., 2023). AI-enhanced surgery tools, such as the Da Vinci Surgical System, can improve surgery accuracy by around 16.3% and reduce surgery times in over 57% of cases [9]. Remote patient monitoring systems, particularly those powered by AI, have been shown to decrease patient visits to physicians by 47% and reduce hospital admissions of elderly patients by 40% (Morrish et al., 2023). Predictive analytics can also forecast in-hospital mortality with an AUC-ROC of 0.86 (Li et al., 2025). AI-powered systems can detect early signs of diseases like Alzheimer's, COPD, and kidney disease years before symptoms appear, allowing for timely interventions (Tang & Sirota, 2024). Furthermore, AI-driven systems have demonstrated the ability to detect diseases like skin cancer and diabetic retinopathy with accuracy comparable to that of experienced clinicians (Esteva et al., 2017). These advancements support the shift toward more personalized and preventive care models, allowing for timely, data-informed decisions that improve the trajectory of treatment and recovery. Additionally, wearable devices and mobile health applications have empowered patients—particularly those with chronic conditions—to monitor and manage their health actively, leading to better adherence to care plans and fewer hospital readmissions (Kvedar et al., 2016).

Cost-Effectiveness. The implementation of new technologies in healthcare also shows promise in terms of cost-effectiveness. AI-driven automation of administrative tasks, such as managing patient records and scheduling appointments, has the potential to save billions annually (Lavoie-Gagne et al., 2025). AI can also improve the speed and accuracy of detecting fraudulent Medicare claims, leading to significant financial savings (Florida Atlantic University, 2023). Predictive analytics can optimize resource allocation in hospitals, improve the accuracy of health insurance rate calculations, and prevent fraudulent insurance claims, contributing to overall cost reduction (Nwosu, 2025). Telemedicine has been found to be a cost-effective alternative for delivering outpatient care, reducing costs for both patients and the healthcare system.

Workforce Shift. These technological changes are also reshaping the healthcare workforce. The integration of new technologies will inevitably lead to a shift in the healthcare workforce, requiring new skills and professions. While technology is not expected to replace healthcare professionals entirely, it will augment their capabilities and change the nature of their tasks (World Economic Forum, 2023). Tasks traditionally performed by physicians or nurses—such as triaging patients, interpreting test results, or providing follow-up instructions—can now be supported or automated by intelligent systems. The automation of administrative processes such as scheduling, billing, and documentation has reduced the burden on clinical staff, freeing up time for patient interaction and care delivery. In fact, AI will likely minimize the time physicians and nurses spend on routine administrative tasks, allowing them to focus more on direct patient care (Bundy et al., 2024). This shift allows human resources to be reallocated to more complex, relational, or supervisory roles, contributing to a more flexible and resilient workforce model (OECD/European Union, 2020). Moreover, remote care models and telemedicine have the potential to redistribute workloads geographically, reduce provider burnout, and expand access to underserved areas (Whitelaw et al., 2020). New tech-based roles are expected to emerge, such as telemedicine specialists, healthcare data analysts, AI and robotics technicians, and cybersecurity experts. While some roles may evolve or be replaced by automation, digital technologies are more likely to augment human capabilities rather than eliminate them. The effective use of AI and data analytics can enhance clinical decision-making and operational efficiency, but human judgment, empathy, and communication remain essential in patient care. This balance between technology and the human element will be central to the success of digital transformation in healthcare.

Education and Reskilling. Healthcare professionals will need to develop new skills and training, particularly in data literacy, human-machine interaction, and ethical oversight, including skills in using EHR systems, telemedicine platforms, and AI and data analytics applications (Doll et al., 2024). Continuous professional development programs will need to evolve to incorporate training on these new technologies and skills. To prepare the healthcare workforce for the digital future, significant efforts in education and reskilling will be required (Ferreira et al., 2025). Healthcare professionals must now collaborate across interdisciplinary teams in increasingly complex digital ecosystems. As Topol (2019a,b) notes, this transformation necessitates a rethinking of medical education and continuous professional development to prepare workers for a technology-augmented clinical environment. Healthcare institutions will need to offer comprehensive training programs catering to various skill levels, from basic digital literacy to advanced specialist programs in areas like clinical informatics and data science. Governments can play a key role by creating policies and incentive schemes to support the digital transformation of healthcare services and promote digital upskilling and retraining of healthcare professionals (McKinsey & Company, 2019). Partnerships between academia and industry will be crucial for developing relevant curricula and ensuring that healthcare professionals acquire the necessary skills to work effectively with new technologies (Brooks, 2023). To fully realize the potential of digital health innovation, healthcare systems must invest not only in new technologies but also in the training and support of their workforce. Infrastructure development, equitable access to digital tools, and ethical considerations around data use are equally crucial to ensuring that these innovations translate into meaningful and inclusive improvements. In the years ahead, the synergy between technological advancement and human-centered care will be a defining feature of successful healthcare systems.

Social Benefits. The social benefits of new technologies in healthcare are wide-ranging. Telemedicine can improve access to care for underserved rural areas and vulnerable populations, breaking down geographical barriers and reducing health inequities. AI-assisted medical services can also benefit these underserved areas (Cruickshank, Wade & Bajwa, 2024). AI can help overcome language barriers in healthcare settings through translation capabilities (Genovese et al., 2024). Digital health interventions can empower patients to actively manage their health and boost their participation in shared decision-making (Pierce et al., 2025). AI-driven tools can also help to assess ambulance needs and optimize resource allocation, ensuring timely medical assistance (Selvan et al., 2025). Furthermore, AI has the potential to reduce human decision-making biases in healthcare, contributing to more equitable care.

The integration of digital technologies also brings important implications for healthcare expenditure. While some innovations entail high upfront investments in infrastructure, software, and training, their long-term use may yield cost savings through reduced hospitalizations, better disease management, and improved workflow efficiencies (Meskó et al., 2017). For instance, predictive analytics can help optimize resource allocation and identify at-risk populations early, thereby reducing unnecessary procedures and admissions (Rajkomar et al., 2019). Nonetheless, there is a risk of widening disparities if these technologies are unevenly adopted or if cost savings are not reinvested equitably.

Finally, while the potential benefits of digital health are substantial, their realization depends on appropriate regulatory frameworks, interoperability standards, and governance mechanisms. Ensuring the safe, equitable, and effective deployment of these tools requires cross-sector collaboration and strong leadership from both health institutions and policymakers. In sum, digital technologies are catalyzing a fundamental transformation in how care is delivered, measured, and experienced. They hold promise not only for improving clinical outcomes but also for reshaping the healthcare workforce and promoting financial sustainability. Realizing this potential, however, requires thoughtful planning, inclusive design, and continuous evaluation to ensure that innovation supports both efficiency and equity in healthcare systems.

8. Regulating Innovation in the Healthcare Sector

As we have seen above, digital medicine is at the forefront of a profound transformation in healthcare delivery. The rapid acceleration of digital innovation in healthcare presents a profound challenge to existing regulatory frameworks, particularly in national health systems such as the NHS. By integrating technologies such as artificial intelligence, mobile health applications, wearable sensors, telemedicine platforms, and genomics into everyday clinical practice, digital medicine promises to radically improve how care is delivered, accessed, and experienced. While these tools hold immense promise for improving patient outcomes, system efficiency, and equity, they also introduce significant risks related to safety, accountability, data governance, and ethical compliance. However, the swift and disruptive nature of these innovations has outpaced the capacity of traditional regulatory frameworks to ensure their safe, equitable, and ethical deployment.

Regulation plays a dual role in this context: it must safeguard public trust and patient safety while also enabling innovation and system responsiveness. In the NHS, this balancing act has become increasingly complex as digital technologies blur the boundaries between medical devices, consumer health tools, and data platforms (Nuffield Council on Bioethics, 2018). Traditional regulatory models—designed mainly for pharmaceuticals and hardware-based devices—struggle to accommodate the iterative nature of AI algorithms, the decentralized nature of digital platforms, and the shifting locus of care from hospitals to homes and smartphones (Topol, 2019a,b).

Historically, healthcare regulation has evolved to address the safety, efficacy, and quality of more conventional technologies, such as pharmaceuticals and medical devices. These tools are typically well-defined, subject to lengthy clinical trials, and relatively stable in their behavior once approved. In contrast, digital technologies often function in real-time, involve adaptive machine learning systems, and operate in highly data-rich environments. As such, regulating digital medicine requires rethinking not just the tools of oversight but the very principles underpinning health governance in the digital age.

The role of regulation in digital medicine is more critical than ever, given the complex, interconnected nature of these technologies and the potential risks they pose to patients and health systems if left unchecked. The principal aims of regulation—ensuring public safety, promoting transparency, securing data integrity, and fostering public trust—must be maintained and extended to new areas introduced by digital innovation. Without appropriate regulatory mechanisms, the benefits of digital medicine may be undermined by unintended harms, including the misuse of personal data, exacerbation of health disparities, or the deployment of untested or ineffective technologies.

8.1 Emerging Regulatory Frameworks and Approaches

In response to these emerging needs, regulators in various jurisdictions have begun to adapt their approaches. In the European Union, the proposed Artificial Intelligence Act represents one of the most comprehensive efforts to date to regulate AI technologies, including their use in health. This proposal introduces a risk-based framework in which AI applications are categorized according to the level of risk they pose to users. Medical AI tools are typically classified as high-risk, which subjects them to stricter regulatory scrutiny, including requirements for transparency, human oversight, and post-market monitoring (European Commission, 2021).

In the United States, the Food and Drug Administration (FDA) has established the Digital Health Center of Excellence, an initiative aimed at developing regulatory science and guidance for the safe and effective use of digital health tools. The FDA has also explored the use of "software precertification" models that streamline the approval process for developers with proven track records of quality and responsibility while still maintaining rigorous safety standards (FDA, 2020).

In the United Kingdom, the Medicines and Healthcare products Regulatory Agency (MHRA) has updated its approach to covering Software as a Medical Device (SaMD), including AI-driven tools. Concurrently, the

National Institute for Health and Care Excellence (NICE) has issued a comprehensive evidence standards framework for evaluating digital health technologies. This framework assesses both the clinical and economic value of digital interventions, aiming to ensure that innovations deliver meaningful benefits to patients while representing an efficient use of public resources (NICE, 2022).

One of the key regulatory challenges is the assessment of safety and effectiveness in real-world settings. AI-driven clinical decision tools, for instance, may evolve through machine learning after deployment, raising questions about how to ensure continued compliance with safety standards (Hatherley, 2020). Regulatory bodies such as the MHRA and NICE are increasingly tasked with developing agile frameworks that can account for "adaptive algorithms" and software as a medical device (SaMD). The recent establishment of the NHS AI Lab and its Regulatory Sandbox initiative reflects a growing institutional recognition of the need for collaborative, flexible, and anticipatory regulatory models (NHSX, 2021).

In parallel, data governance has emerged as a cornerstone of digital health regulation. One of the defining features of digital medicine is its reliance on real-time data collection and analysis. Many digital health tools function continuously and adaptively, drawing on user inputs, environmental data, or system feedback to modify their outputs. This continuous evolution means that regulatory assessments must also be continuous, capable of tracking post-deployment behavior and ensuring long-term reliability and safety. Static models of regulatory approval, based on pre-market evaluation alone, are increasingly inadequate for overseeing the dynamic nature of digital technologies. With increasing reliance on large-scale patient data—often stored in cloud-based systems or shared across providers—ensuring the integrity, security, and privacy of health information is paramount. The UK General Data Protection Regulation (UK GDPR), which aligns with the EU's framework, mandates strict rules around data processing, consent, and patient rights. However, operationalizing these principles in dynamic, data-rich environments like those generated by real-time health monitoring or predictive analytics remains a significant challenge (Morley, Machado et al., 2020).

Furthermore, the sensitive nature of health data, which is central to the functioning of most digital health applications, raises urgent questions about privacy and data protection. Regulations must, therefore, address not only the performance of technologies but also the ethical and legal dimensions of data governance. This includes the way in which data are collected, stored, shared, and interpreted, particularly when algorithms are involved in making or supporting clinical decisions. As digital medicine becomes more reliant on predictive analytics and AI-driven recommendations, the need for stringent, clearly defined regulatory standards becomes paramount.

8.2 Persistent Regulatory Challenges

Despite these promising developments, a number of unresolved challenges persist. One of the most pressing is the discrepancy between the speed of innovation and the pace of regulatory adaptation. Technological change, particularly in digital health, is moving rapidly. New applications, updates, and iterations regularly emerge, while regulatory processes often remain slow, deliberative, and reliant on lengthy evidence-generation cycles. This mismatch can result in delays in the deployment of beneficial technologies or, conversely, the premature release of insufficiently vetted tools into clinical practice.

Another significant challenge is the lack of transparency in algorithmic processes. Many AI-driven systems function as "black boxes," offering little visibility into how outputs are generated. This opacity complicates regulatory evaluation, especially in clinical contexts where the rationale behind a recommendation or diagnosis must be clear and defensible. When clinicians are expected to trust or act upon AI-generated insights, regulators must ensure that these systems are not only accurate but also explainable and accountable (Hatherley, 2020; Leslie, 2021). In addition to technical and procedural challenges, the regulation of digital medicine must contend with profound ethical concerns. These include questions about equity and access, particularly for populations that may lack digital literacy, reliable internet connectivity, or access to

smart devices. Regulators must ensure that digital innovation does not deepen existing health inequalities but rather contributes to more inclusive and equitable health systems.

Moreover, the globalization of digital health technologies raises questions about harmonization. While some jurisdictions move quickly to regulate, others lag behind, resulting in regulatory fragmentation. This inconsistency can hinder the development of international markets, reduce clarity for developers, and complicate the implementation of cross-border digital health solutions. Greater alignment in international standards and regulatory cooperation is urgently needed to support the responsible globalization of digital medicine (WHO, 2021).

Looking ahead, the future of regulation in digital medicine will depend on the ability of institutions to embrace adaptive governance—a model that allows for regulatory flexibility while maintaining core principles of safety, efficacy, and equity. Adaptive governance involves continuous learning, feedback loops, stakeholder engagement, and iterative policymaking. Mechanisms such as regulatory sandboxes—controlled environments where new technologies can be tested under supervision—offer valuable models for balancing innovation with oversight. Equally important is the integration of ethics into regulatory design. As digital health tools become more pervasive, regulators must consider not only how these tools function technically but also how they shape relationships between patients and providers, affect autonomy and consent, and influence clinical judgment. Ethical frameworks, such as those proposed by the Alan Turing Institute and others, can provide foundational principles for responsible regulation and guide the development of policies that reflect both technological realities and societal values (Floridi et al., 2018).

In conclusion, regulation in digital medicine is not an afterthought; it is a central pillar of sustainable innovation. As healthcare systems increasingly rely on digital tools to address challenges of access, efficiency, and quality, the need for thoughtful, robust, and future-oriented regulation becomes more urgent. Regulatory institutions must evolve alongside the technologies they oversee, adopting adaptive models of oversight, fostering transparency, protecting individual rights, and ensuring equitable access to the benefits of digital health. Only through such a coordinated and principled approach can digital medicine fulfill its promise to transform healthcare for the better.

8.3 Regulation of Large Language Models in Healthcare: Navigating Emerging Challenges

The rapid advancement of large language models (LLMs) has spurred considerable excitement about their potential to transform healthcare delivery. LLMs—sophisticated artificial intelligence systems that generate human-like text—are being explored for an array of applications, ranging from patient education and communication to clinical documentation and decision support. Specifically, LLMs are being explored for tasks such as answering patient queries, summarizing or translating complex medical texts, and supporting documentation processes (Rathnayake et al., 2023). Their capacity to interpret and produce natural language aligns closely with patient-centered care goals, including accessibility, personalization, and informed decision-making. However, as these technologies become more integrated within healthcare systems, significant regulatory challenges have emerged that demand scrutiny. These challenges encompass issues of safety, accuracy, transparency, data privacy, and the ethical use of patient information, calling for the development of adaptive and robust regulatory frameworks.

It is important to distinguish between regulatory frameworks developed for artificial intelligence (AI) broadly and those that are (or should be) tailored to LLMs specifically. General AI regulation often focuses on risk classification, transparency, and explainability in algorithmic decision-making. However, LLMs present unique regulatory concerns due to their generative nature, probabilistic outputs, and unpredictability in language generation. Unlike AI systems trained for narrow, rule-based tasks (e.g., image classification), LLMs operate with vast, generalized language corpora and can produce unstructured text that mimics human discourse without providing verifiable reasoning or clinical grounding (Leslie, 2021). This introduces

regulatory blind spots around the authorship, reliability, and legal accountability of outputs—especially when LLMs are embedded in clinical decision support tools or used directly in patient communication. Regulatory frameworks must, therefore, include content auditing, usage boundaries, and domain-specific fine-tuning requirements that account for the distinctive risks LLMs pose in healthcare contexts.

According to Meskó & Topol (2023), LLMs in healthcare face unique regulatory hurdles compared to more traditional AI applications. Their generative nature means that LLMs do not simply classify or predict outcomes but actively produce text-based content. These characteristics raise concerns over the accuracy and completeness of the information provided, especially when the language output informs clinical decisions or patient self-management. As highlighted in the article, cases of biased, incomplete, or even potentially misleading outputs underscore the risk that LLMs pose if their use is not adequately controlled. Busch et al. (2025) have conducted a recent systematic review of 89 studies across 29 medical specialties (conducted between 2022 and 2023) where they find that while LLMs are already being tested in clinical and patient-facing contexts, most are not optimized for medical environments. Critical concerns include a lack of transparency in data provenance, limited adaptation to clinical language, and insufficient safeguards to ensure output accuracy. These issues raise ethical and safety questions, particularly as LLMs may generate content that is inaccurate, incomplete, or biased, potentially misleading both patients and clinicians (Hatherley, 2020; Morley et al., 2020).

Moreover, the opacity of LLMs—often described as the "black box" problem—complicates the regulatory process. Traditional regulatory frameworks are typically geared toward static, well-understood technologies. In contrast, LLMs are dynamic, frequently updated systems that continuously learn from new data inputs. This fluidity challenges existing approval processes and demands continuous monitoring and post-deployment audits (Leslie, 2021). Furthermore, the data used to train these models often include sensitive patient health information, making compliance with existing data protection regulations, such as the UK GDPR and HIPAA in the United States, a critical but complex issue (Morley, Floridi et al., 2020; Morley, Machado et al., 2020).

Given these challenges, regulation must play a multi-faceted role, and it is pivotal in governing the development and deployment of LLMs in healthcare. Regulatory oversight must address not only traditional dimensions of medical device safety and efficacy but also novel considerations such as algorithmic bias, explainability, and dynamic learning. Unlike conventional medical technologies, LLMs may evolve post-deployment—changing their behavior in response to new data or updates—which challenges static approval models and demands continuous monitoring mechanisms (European Commission, 2020b).

First and foremost, regulation should ensure that LLMs deployed in healthcare are safe and effective. This involves not only the initial approval based on technical performance and clinical validation but also establishing mechanisms for ongoing monitoring to capture any deviations from approved behavior as the models evolve. Regulatory bodies need to implement guidelines that require transparency in the training data and decision-making processes of LLMs, along with clear accountability for any errors or adverse outcomes (European Commission, 2021).

Second, regulatory frameworks should address issues of data governance. With the increasing reliance on vast datasets, proper handling of patient data becomes paramount. Regulations must stipulate robust data anonymization techniques and secure data-sharing protocols. Furthermore, ethical oversight is required to ensure that the benefits of LLMs—such as improved patient education and streamlined clinical workflows—do not come at the expense of patient autonomy or privacy (WHO, 2021).

Third, the regulation of LLMs needs to be adaptive. Because these models can evolve post-deployment, static regulatory approval is insufficient. Instead, regulators should consider adaptive regulatory frameworks—such as regulatory sandboxes and real-time performance audits—that allow experimentation under controlled conditions while ensuring patient safety (Hatherley, 2020). This adaptive approach also

provides a mechanism for the periodic re-evaluation of LLMs to keep pace with technological advancements and evolving clinical contexts.

Moreover, LLMs pose complex challenges related to data privacy and consent, particularly when trained on or applied to sensitive health data. Compliance with data protection laws such as the UK GDPR and HIPAA in the U.S. is not always straightforward, especially when model training involves indirect exposure to identifiable information (Leslie, 2021). In this context, frameworks such as the EU's proposed AI Act and the WHO's guidance on trustworthy AI in health are essential in shaping future regulatory responses (European Commission, 2021; WHO, 2021).

In summary, the integration of LLMs into healthcare holds transformative promise but also presents significant regulatory challenges. A comprehensive regulatory framework must not only ensure safety, efficacy, and transparency but also be dynamic enough to respond to the continually evolving nature of these technologies. Policymakers, regulatory agencies, and healthcare providers need to work in tandem to develop adaptive regulatory models that balance the benefits of innovation with the imperatives of patient safety, data governance, and ethical use. As the digital revolution accelerates, the ongoing evolution of regulation will be critical in shaping how LLMs and other digital health technologies ultimately contribute to improved healthcare outcomes and more efficient healthcare systems. Ultimately, effective regulation must strike a balance between innovation enablement and risk mitigation. Regulatory sandboxes, algorithmic impact assessments, and interdisciplinary oversight bodies may offer pathways for safe experimentation and iterative improvement. Given their far-reaching implications, LLMs should be subject to a robust, context-sensitive regulatory regime that evolves alongside the technologies themselves, prioritizing transparency, accountability, and patient safety.

8.4 The Role of Health Technology Assessment in Digital Medicine

The evaluation of value for money and cost-effectiveness in digital health interventions requires new approaches. Traditional health technology assessment (HTA) methods, which are often based on static clinical trials and fixed pricing models, may not be well-suited to rapidly evolving technologies with complex pricing structures or data-driven value creation (Drummond et al., 2020). The rapid rise of digital medicine and diverse functionalities pose unique challenges to traditional methods of evaluating medical technologies. In this evolving context, Health Technology Assessment (HTA) must adapt to ensure that digital health interventions are rigorously assessed for their safety, effectiveness, value for money, and broader ethical and societal impacts. HTA is a multidisciplinary process that systematically evaluates the medical, social, economic, and ethical implications of the development, diffusion, and use of health technologies. Historically, HTA has focused on pharmaceuticals, medical devices, diagnostic tests, and surgical procedures. The core objectives have remained consistent: to inform decision-making by payers, policymakers, and clinicians, ensure the optimal allocation of limited resources, and promote evidence-based adoption of new technologies (Drummond et al., 2015).

With the expansion of digital medicine, HTA now faces new frontiers. Unlike conventional health technologies, many digital interventions are software-based, data-intensive, and iterative in nature, often updated in real-time or through machine learning mechanisms. These characteristics challenge static, one-time assessments and call for more dynamic and lifecycle-based HTA frameworks. Assessing digital health technologies requires expanding the methodological scope of HTA in several key ways. First, traditional clinical trials may be ill-suited to evaluate many digital tools, particularly mobile apps or AI-driven systems that evolve rapidly or operate in decentralized care settings. Alternative methodologies—such as real-world evidence (RWE) studies, pragmatic trials, or adaptive designs—may be more appropriate, though they also introduce complexity in data interpretation and generalizability (Husereau et al., 2022).

Second, the value proposition of digital medicine often lies not solely in clinical outcomes but in improvements to care pathways, workflow efficiency, patient empowerment, or remote accessibility. These

domains are less readily captured by standard measures such as quality-adjusted life years (QALYs) or cost-per-case avoided. As such, HTA must increasingly integrate patient-reported outcomes, user experience metrics, and qualitative evidence to fully appraise the utility of digital interventions (Taylor et al., 2021).

Third, digital health technologies pose distinct implementation and scalability challenges, including issues related to interoperability, cybersecurity, workforce readiness, and regulatory compliance. An effective HTA of digital medicine must, therefore, consider not only the intrinsic merit of a given technology but also the contextual conditions necessary for its successful deployment and sustained impact within health systems.

Economic evaluation—a central component of HTA—must also evolve to accommodate digital medicine. Traditional models of cost-effectiveness may be constrained when applied to technologies with non-linear cost structures, such as those involving subscription models, cloud-based storage, or variable costs tied to usage levels. Moreover, many digital tools may exert indirect or long-term benefits, such as reduced hospital readmissions or improved chronic disease management, which are difficult to quantify within conventional evaluation timeframes. In light of these complexities, HTA agencies such as NICE in the UK have introduced modified evidence frameworks for digital health technologies. These frameworks propose tiered levels of evidence requirements depending on the potential risk, complexity, and intended purpose of the technology (NICE, 2022). They also emphasize the importance of early dialogue between developers and regulators to align evaluation standards with innovation cycles.

HTA in digital medicine must also engage with ethical, legal, and societal dimensions that are increasingly central to public and policy debates. This includes algorithmic transparency, bias mitigation, equitable access, and the preservation of the clinician-patient relationship in increasingly automated contexts (Floridi et al., 2018). For example, AI-based clinical tools raise concerns about algorithmic bias, explainability, and the shifting boundaries of clinical responsibility. Digital therapeutics and mental health apps raise questions about privacy, surveillance, and the digital divide. These issues necessitate the inclusion of ethical impact assessments and stakeholder engagement processes within the HTA framework (Refolo et al., 2021). Furthermore, all public healthcare systems, as public institutions with a strong equity mandate, must ensure that digital innovation does not exacerbate existing health disparities or create new forms of exclusion due to digital illiteracy, infrastructure gaps, or algorithmic bias. In addition, the distributional consequences of digital innovation must be assessed. While digital tools may expand access for some populations, they may simultaneously exclude others—particularly those with limited digital literacy, language barriers, or inadequate internet access. A comprehensive HTA should examine the equity implications of digital technologies and offer guidance on mitigating health disparities.

Given the dynamic and multidimensional nature of digital health interventions, HTA is increasingly being reconceptualized as a continuous and iterative process rather than a single decision point. This approach, sometimes referred to as "lifecycle HTA", emphasizes early dialogue, ongoing monitoring, and post-market reassessment as key components of responsible health innovation governance (Oortwijn et al., 2017). Such models recognize that the performance and value of digital technologies can evolve significantly over time and that their successful integration into healthcare systems depends on contextual, behavioral, and infrastructural factors. This shift also aligns with the growing emphasis on adaptive regulation, in which HTA is integrated with real-time data collection, stakeholder feedback, and conditional approval mechanisms. By embedding HTA within broader digital governance structures, health systems can more effectively balance innovation with oversight, fostering environments that encourage both experimentation and accountability.

One of the distinguishing features of DTx is their dependence on sustained user engagement for therapeutic efficacy. Factors such as user interface design, personalization, feedback mechanisms, and digital literacy can all influence adherence. HTA must, therefore, consider behavioral science and usability studies as part of the

clinical assessment process (Kumar et al., 2013). High attrition rates may significantly reduce real-world effectiveness even when trial results are positive.

Digital therapeutics often process sensitive health data, raising concerns about privacy, data governance, and interoperability with existing health information systems. These dimensions are increasingly incorporated into HTA, particularly under frameworks like the EU GDPR, which mandates strict data protection protocols (European Commission, 2020a). Ethical issues such as algorithmic bias, unequal access, and the commercialization of health data also require scrutiny. Some HTA bodies have begun to develop tailored frameworks for DTx evaluation. In Germany, the Federal Institute for Drugs and Medical Devices (BfArM) has introduced the DiGA fast-track process, which allows temporary reimbursement of DTx pending further evidence of benefit. Similarly, NICE in the UK has developed the Evidence Standards Framework for Digital Health Technologies, which outlines tiered evidence requirements based on clinical risk and intended purpose (NICE, 2022). These frameworks signal a shift toward more adaptive and iterative HTA models, which recognize the dynamic nature of software and the need for continuous data collection and evaluation post-launch.

Despite progress, significant challenges remain. The heterogeneity of DTx, the lack of standardized outcome measures, and the need for long-term data complicate comparative assessments. Furthermore, capacity gaps within HTA organizations—particularly regarding digital literacy and software evaluation expertise—may hinder effective appraisal. To address these issues, there is a growing call for international harmonization of HTA methodologies, greater investment in HTA workforce development, and stronger collaboration between regulators, payers, developers, and patients. Real-time data-sharing platforms, post-market monitoring systems, and hybrid evaluation models may offer pathways toward more responsive and informed decision-making. As digital innovations proliferate and diversify, HTA methodologies must evolve to capture their unique characteristics, assess their real-world performance, and respond to the ethical, societal, and economic questions they raise. Through the development of adaptive, inclusive, and interdisciplinary frameworks, HTA can continue to provide a robust foundation for evidence-informed decision-making in the digital age of medicine.

9. Healthcare Technologies and Costs

Health technology has long been blamed for its important impact on rising healthcare costs. With its increasing complexity in recent decades, accompanied by unprecedented scarce public finances, it will continue to receive much attention from economists. While healthcare sustainability is at risk, health technology may represent both the source and the solution to the problem of mounting costs. An overwhelming number of health innovations have proven to be cost-effective and game-changing for vast portions of the world's population. However, it is less clear to what extent their introduction has indeed delivered enough value to patients and societies. The challenges for policymakers will evolve around the proper identification of technologies with adequate benefits vs. affordability, conditional on safety. On the one hand, identification is likely to be more productive if scanning of the possible technologies under development is undertaken. On the other hand, policy efforts will have to provide incentives to invest in technologies that are relevant from the social welfare point of view. Among the most innovative health technology domains, such as health information technology and precision medicine, it is utterly unclear how their evolution will shape future healthcare. Nevertheless, already acknowledged promises of digital health are likely to provide important cost reductions in the provision mechanisms of many services.

A substantial body of economic literature identifies technological advancement as a primary determinant of increasing healthcare expenditures. Building upon the seminal work of Newhouse (1992), researchers have extensively investigated this relationship. The adoption and rapid diffusion of medical technologies are widely recognized as key drivers of expenditure growth (Cutler & McClellan, 1998; Newhouse, 1992; Okunade & Murthy, 2002; Weisbrod, 1991), with estimates attributing between 30% and 70% of cost

increases to novel technologies (Australian Productivity Commission, 2005; Barros, 1998; Congressional Budget Office, 2008; Pestieau, 2006). Empirical evidence suggests that spending growth exhibits a stronger correlation with the introduction of innovative, high-cost technologies than with the escalating costs of existing treatments (Cutler & McClellan, 1996; Cutler et al., 1998).

While some scholars, including Berndt et al. (2002), Cutler (2004), and Lichtenberg (2014, 2016, 2017), have demonstrated that even costly innovations can yield significant improvements in survival rates and overall health outcomes, a more nuanced perspective is warranted. Cutler, Rosen & Vijan (2006) concluded that healthcare spending prior to 1960 generally represented a judicious allocation of resources, whereas expenditures on the older population after 1980 incurred exceedingly high costs per life-year gained. Furthermore, Skinner & Staiger (2015) emphasize that even subtle variations in technology adoption patterns can exert a substantial influence on outcomes and productivity, particularly in instances where innovations exhibit cost-effectiveness.

The Organization for Economic Co-operation and Development (OECD) has similarly observed that technological advancements contribute to escalating healthcare costs (OECD, 2017). New technologies not only command higher prices but also tend to expand the volume of services provided rather than merely substituting for existing procedures, thereby sustaining expenditure growth. Since the 1970s, healthcare spending in OECD countries has grown at a rate exceeding GDP growth by 2%, with healthcare accounting for 17.6% of GDP in the US in 2023. Projections indicate that this figure may approach 20% by 2032. Research from the Kaiser Family Foundation has further revealed that greater availability of medical technologies is frequently associated with heightened utilization rates and increased healthcare spending (Kaiser Family Foundation, 2007). For instance, an increase in the number of MRI units has been correlated with higher utilization and spending on diagnostic imaging services. Moreover, the integration of new technologies into healthcare systems often necessitates substantial upfront investments and can lead to increased operational costs.

Although these technologies hold the potential to enhance patient care and outcomes, they concurrently contribute to the overall rise in healthcare expenditures. However, scholarly work by Becker (2007), Becker, Philipson & Soares (2005), Murphy & Topel (2003), and Nordhaus (2002) suggests that the economic benefits accruing from increased life expectancy and improved health status outweigh the costs associated with technological investment. From this vantage point, the economic value of health innovation appears to supersede its financial burden. Nevertheless, the challenges of overuse and inefficiencies in the adoption of new technologies remain salient.

According to Chandra & Skinner (2012) and Skinner & Staiger (2015), the health benefits derived from technological adoption are contingent upon the cost-effectiveness of individual innovations. Not all technologies yield proportional gains in outcomes or efficiency (Cutler, 2004). Chandra & Skinner (2012) proposed a framework categorizing technologies into (1) universally effective innovations offering high value at low cost (e.g., antibiotics); (2) targeted, high-cost innovations that are efficient when properly applied (e.g., angioplasty); and (3) marginally effective technologies incurring high costs with limited benefits (e.g., proton beam therapy for prostate cancer).

The inherent difficulties in evaluating cost-effectiveness, coupled with the often-generous reimbursement models prevalent in both public and private healthcare systems, have contributed to the widespread diffusion of technologies based on novelty rather than demonstrated value. As technology simultaneously stimulates supply (by offering new treatment options) and demand (particularly when patient costs are subsidized), it frequently drives up total expenditures in ways that may not be commensurate with improvements in patient outcomes. To ensure the long-term sustainability of healthcare systems, it is imperative to rigorously assess the clinical value of treatments, particularly in the context of aging populations and escalating healthcare needs. Rigorous evaluation tools—such as clinical trials, health

technology assessments, cost-effectiveness analyses, and real-world evidence—are indispensable for understanding the population-level impact of innovations and guiding optimal resource allocation. The OECD (2017) has observed that the cost-effectiveness of new medical technology has diminished over the past century, with rising prices and declining incremental benefits.

In the context of emerging digital technologies, the central question revolves around whether these innovations offer not only the promise of improved outcomes but also enhanced efficiency. AI-driven diagnostics, remote monitoring, and predictive analytics have the potential to streamline clinical decision-making, reduce unnecessary hospital admissions, and optimize the utilization of medical resources, thereby potentially alleviating the financial burden on both healthcare systems and patients. However, the realization of these cost-saving benefits is not guaranteed. The deployment of such technologies necessitates thoughtful planning, robust infrastructure, and regulatory oversight to ensure that efficiency gains do not compromise equity, access, or quality. Without deliberate policy interventions, there exists a tangible risk that innovation could exacerbate existing disparities rather than ameliorate them.

Empirical research tackling this issue has followed several methodological directions. One widely used approach involves macro-level observational and econometric analyses that correlate aggregate digitalization indicators with national health spending outcomes. For instance, Ndubizu et al. (2011) analyzed data from 148 countries to examine how internet and personal computer use influenced healthcare expenditures in both public and private healthcare sectors, highlighting that the impact of digital infrastructure on health costs is not uniform but is instead significantly mediated by institutional features such as corruption and investor protections. Building on this international perspective, Kuzior et al. (2024) utilized panel regression models for 31 European countries to quantify the influence of digital determinants, such as internet access and innovation indices, on public health indicators and some aggregate expenditure measures. Although their primary dependent variables included life expectancy and self-rated health status, their application of macro-panel data reflects the field's increasing ability to capture system-level digital impacts.

Complementing these observational studies are simulation-based and cost-benefit analyses, which are particularly prominent in European research consortia. Stroetmann et al. (2007) conducted cost-benefit analyses of ten e-health applications implemented in various European countries, reporting that positive net benefits materialized over an average of five years—a timeline that highlights the necessity of medium- to long-term investment perspectives when assessing digitalization efforts. Notably, the return on investment varied by intervention, taking as little as two years for teleradiology and as long as seven years for national electronic patient records. Zamora (2012) advanced this approach with an international impact assessment of telehealth for chronic conditions, applying break-even modeling to assess when hospitalization savings would offset daily monitoring costs and synthesizing evidence from leading country exemplars such as the UK and Italy.

At the national level, risk-oriented and simulation models further illuminate the financial implications of digital medicine. Sendek (2014), focusing on Slovakia, integrated both empirical data and projected financial scenarios to estimate the ten-year net present value of an e-health system encompassing EHRs, e-prescribing, e-referrals, and a national health portal. Cumulative projections suggested notable system-wide savings, but the specificity to one country and focus on conventional e-health functions limited the generalizability to broader definitions or international contexts. In a more recent contribution leveraging quasi-experimental techniques, Han et al. (2023) examined the effect of China's Broadband policy on healthcare expenditures using a difference-in-differences approach. Their analysis of microdata from 2010 to 2018 found that digital infrastructure investment was associated with an 18.8% reduction in healthcare spending among urban populations in pilot cities, with mechanisms likely related to improved insurance access and greater efficiency. While powerful, such single-country analyses emphasize the contingent nature of outcomes and their dependence on policy context. Similarly, studies from England utilizing randomized

controlled trials have evaluated the cost-effectiveness of telehealth and telecare at a system level, finding only limited evidence for cost savings without more integrated service redesign (Henderson, 2018).

To synthesize and interpret the economic evidence at a broader scale, recent reviews and meta-analyses have aggregated cost-effectiveness data across multiple digital health interventions. Shah (2024) employed a mixed-methods and random-effects meta-analytic approach, pooling incremental cost-effectiveness ratios (ICERs) and benefit-cost ratios (BCRs) from global studies examining telemedicine, AI-health, and EHR-related interventions. While these reviews highlight both potential efficiency gains and challenges related to equity and access, most do not provide direct quantitative projections of macro-level health expenditure impacts. Sülz et al. (2021) conducted a scoping review of economic evaluations supporting independent living among older people, cataloging the range of direct and indirect cost categories considered. However, the review focused primarily on intervention-level analyses and did not attempt to quantify system-wide expenditure effects or offer forward-looking projections. Policy and modeling frameworks, such as those put forth in Codagnone et al. (2011), underline the urgent need for more sophisticated system dynamics and microsimulation methods to bridge the gap between conceptual benefit and validated macroeconomic impact—an agenda further complicated by persistent data and definitional limitations.

Finally, the study by Sapanel et al. (2025) offers an innovative approach to addressing the growing concern over rising healthcare costs driven by the integration of digital technologies. Focusing on digital therapeutics (DTx)—software-based medical interventions—the authors present a comprehensive examination of the factors that influence the economic value of DTx, which are software-based medical interventions designed to treat or manage a variety of health conditions. In the context of escalating global healthcare costs, aging populations, and increasing burdens of chronic disease, DTx technologies hold significant promise for improving health outcomes while potentially containing costs. However, their widespread adoption is hindered by the need for robust evidence demonstrating their clinical efficacy and economic value. This article employs a group concept mapping (GCM) methodology to capture the collective perspectives of 62 stakeholders—including healthcare professionals, researchers, industry leaders, and public policy experts—across all stages of the DTx lifecycle, from development and validation to implementation and commercialization. The research identifies 59 specific factors grouped into eight thematic clusters that are perceived to impact DTx economic value. These clusters span early development stages, pre-implementation planning, and real-world deployment. Stakeholders identified two clusters—DTx Impact on Patient Outcomes and DTx Implementation—as the most critical drivers of economic value, though notably, the DTx Associated Costs and DTx Monetization Models clusters were underappreciated in actual decision-making practices, particularly among researchers. This gap suggests a misalignment between what is considered important for DTx success and what is addressed during development and implementation. The study introduces a conceptual framework that visually maps these clusters, illustrating that factors influencing DTx value are multidimensional and distributed throughout the product lifecycle, thus requiring integrated attention from all stakeholders. It also highlights the divergence of perspectives across stakeholder types; for instance, public sector respondents placed a higher emphasis on technology considerations and overall economic impact than their industry counterparts. Moreover, researchers often focused primarily on early development issues while underestimating the importance of costs and monetization strategies—factors that are crucial for achieving market viability. This discrepancy underscores a structural weakness in the current development pipeline for digital health technologies, where insufficient early attention to economic factors can limit eventual adoption and reimbursement. The article suggests that bridging this gap will require interdisciplinary collaboration, particularly involving public-private partnerships, to integrate commercialization expertise earlier in the innovation cycle. From a methodological standpoint, the use of GCM enabled the authors to create a shared conceptual space where diverse stakeholders could articulate and organize complex ideas. This participatory and structured approach yielded not only thematic insights but also a go-zone analysis that identified priority clusters: those that are both

highly important and under-considered in current practice. These insights are critical for informing the policy and strategic frameworks that underpin investment in digital health, especially as healthcare systems worldwide confront increasingly constrained resources and seek high-value interventions. The study's implications extend beyond DTx to the broader question of how new healthcare technologies can be designed, evaluated, and implemented in ways that maximize their contribution to health system sustainability. Given the high costs associated with chronic disease management and the inefficiencies in traditional care delivery models, digital therapeutics represent a potentially transformative solution—provided they are developed with a clear understanding of the economic value drivers across diverse health system contexts. The article, therefore, contributes significantly to the emerging literature on the economic assessment of digital health and underscores the importance of early, multidimensional evaluation frameworks that align technological innovation with real-world health system needs and priorities.

Overall, the current literature reveals that while digital medicine interventions are frequently associated with increased short-term costs due to infrastructure, training, and transition requirements, the realization of net system-level savings is conditional upon comprehensive and integrated implementation, favorable institutional environments, and sufficient time horizons. Causally robust, globally comparative analyses remain rare, and effects are often highly heterogeneous by country, intervention, and adoption context. The field continues to move toward richer empirical designs—incorporating quasi-experimental natural experiments, large-scale panel data, and meta-analytic syntheses—but the balance of evidence remains cautious regarding immediate and universal cost-saving claims.

Furthermore, despite this growing interest in the macro-level economic impacts of digital medicine, several key research gaps remain. Existing studies frequently rely on proxies for digital adoption and predominantly employ observational designs, limiting the ability to make robust causal inferences about the effect of digital medicine on health expenditures at national or global scales (Ndubizu et al., 2011; Kuzior et al., 2024). While some recent single-country analyses utilize quasi-experimental approaches to strengthen causal claims Han et al. (2023), there remains a lack of comparative, harmonized studies across diverse health systems, particularly in low- and middle-income countries (Stroetmann et al., 2007; Ndubizu et al., 2011; Zamora, 2012; Kuzior et al., 2024). Furthermore, the mechanisms through which digital medicine influences health expenditure—such as reductions in hospitalizations versus rising demand from improved access—are not fully elucidated, especially in contexts of partial or fragmented digitalization (Sülz et al., 2021; Han et al., 2023). Although simulation and projection models anticipate long-term cost savings, these claims are rarely validated using longitudinal real-world data, and short-term cost increases are commonly observed (Zamora, 2012; Sendek, 2014). Many studies also face challenges in measurement, often utilizing broad or indirect indicators of digital health and lacking advanced macroeconomic modeling frameworks (Ndubizu et al., 2011; Kuzior et al., 2024; Codagnone et al., 2011). Finally, the equity implications of digital medicine adoption remain underexplored at the macro level, with limited evidence regarding how digital health may reduce or exacerbate disparities in health spending across populations (Sülz et al., 2021; Han et al., 2023). Addressing these gaps will require the application of stronger causal methods, the development of specific and standardized adoption indicators, the expansion of research to underrepresented regions, rigorous model validation, and systematic analysis of the mediating pathways and distributional consequences of digital health interventions.

10. Conclusions

The digital transformation currently underway in healthcare marks a critical juncture in the evolution of health systems, with implications that extend far beyond the adoption of individual technologies. Unlike previous waves of medical innovation—such as the development of antibiotics, imaging technologies, or minimally invasive surgery—which followed relatively linear trajectories and were integrated over decades, the present era is characterized by the rapid and widespread introduction of digital tools. These include artificial intelligence, big data analytics, wearable biosensors, telemedicine platforms, and personalized

genomics. Together, they are reshaping not only how care is delivered and organized but also how it is conceptualized, measured, and experienced by both patients and providers.

For all healthcare systems, this digital disruption presents a dual reality. On the one hand, it offers the potential to dramatically improve health outcomes through earlier diagnosis, more accurate treatment, and better patient engagement. Digital tools can also enable more efficient use of resources, support population health management, and enhance system resilience in the face of growing demand and workforce pressures. On the other hand, these same technologies pose significant risks and challenges. Concerns over data privacy, algorithmic bias, transparency, and uneven access raise urgent ethical and operational questions. Furthermore, many digital solutions have not yet demonstrated consistent clinical effectiveness, nor have they been thoroughly evaluated for their economic and social impacts.

A central conclusion of this analysis is that the existing structures for assessing, regulating, and scaling health technologies are not fully equipped to handle the complexity and speed of digital innovation. Traditional health technology assessment (HTA) frameworks, which rely heavily on controlled trial data and long evaluation timelines, are often ill-suited for dynamic, iterative technologies that evolve post-deployment. Similarly, static regulatory models struggle to keep pace with the adaptive nature of machine learning algorithms and the global distribution of digital health platforms.

To navigate this shifting landscape, healthcare systems must adopt more flexible, responsive, and anticipatory approaches. This includes updating HTA methodologies to incorporate real-world evidence, patient-reported outcomes, and qualitative measures of user experience. It also involves developing regulatory mechanisms that can accommodate continuous updates and enable responsible innovation without compromising safety and equity. At the same time, investments in digital infrastructure, workforce training, and institutional capacity are essential to ensure that technological benefits are not concentrated in a few areas but are distributed equitably across regions and populations.

Crucially, digital transformation should not be understood as a purely technical evolution. It represents a broader governance challenge that requires coordinated action across policy, clinical practice, ethics, and public engagement. If approached strategically, digital technologies can serve not only to modernize care but also to reorient health systems around values of inclusivity, transparency, and sustainability.

In conclusion, the digital disruption of healthcare is both inevitable and transformative. The challenge for the healthcare systems—and health systems globally—is to ensure that the pace of innovation is matched by the development of governance structures capable of harnessing its benefits while mitigating its risks. This calls for a shift in mindset: from passive adoption to proactive stewardship, from fragmented initiatives to systemic integration, and from reactive regulation to anticipatory strategy. Only through such an approach can digital medicine become a driver of not just better care but better health systems.

More critically, policy discussions should shift from justifying rising expenditures to exploring alternative resource allocations. Would investing in education, prevention, or lifestyle interventions yield better health outcomes than expanding high-cost medical treatments? The key question should no longer be "Has increased spending been worth it?" but rather "Could we achieve greater value by reallocating resources?" This debate is particularly relevant given fiscal constraints, demographic shifts, and rising societal expectations for better healthcare. Answering this requires a robust economic framework to evaluate the impact of medical research and innovation on mortality and morbidity —one that is grounded in strong multidisciplinary partnerships across health economics, clinical and technological research, public health, and policy analysis to ensure comprehensive and actionable insights.

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