Review Article

BIOMEDICAL Journal of Scientific & Technical Research

ISSN: 2574 -1241

DOI: 10.26717/BJSTR.2025.64.009977

Long-Term Economic Consequences of Artificial Intelligence Implementation in Healthcare Institutional Performance Management, Effectiveness, and Patient Outcomes-The Importance of Thorough Health Technology Assessment: A Systematic Review

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ARTICLE INFO

Received: November 11, 2025

Published: November 24, 2025

Citation: Dimitrios Karaferis, Dimitra Balaska, Demetra Konstantakopoulou, and Yannis Pollalis. Long-Term Economic Consequences of Artificial Intelligence Implementation in Healthcare Institutional Performance Management, Effectiveness, and Patient Outcomes-The Importance of Thorough Health Technology Assessment: A Systematic Review. Biomed J Sci & Tech Res 64(1)-2025. BJSTR. MS.ID.009977.

ABSTRACT

As global healthcare systems contend with escalating expenses and growing demand, it has become essential to comprehend the financial ramifications of adopting Artificial Intelligence (AI). The gathering of information from patient records, combined with the corresponding clinical evaluation of the AI system, allows specific AI technologies to produce real-time forecasts, providing all pertinent links and sources of information for appropriate recommendations. Consequently, AI is swiftly revolutionizing healthcare delivery, presenting potential not only for improving clinical outcomes but also for maximizing operational efficiency and resource distribution. Given that performance management, cost-effectiveness, and patient outcomes are fundamental components of healthcare institutions, this study seeks to explore how AI methodologies can enhance the outcomes of healthcare facilities and the significance of Health Technology Assessment (HTA) in the appraisal of emerging AI systems. This research constitutes a systematic review encompassing all publications regarding healthcare facilities efficiency from January 2020 to October 2025. The identification of these articles conducted through a search of PubMed/Medline, Scopus, Embase, Web of Science, EconLit, and Google Scholar. Furthermore, the reference lists of these articles were examined to uncover additional pertinent studies. Ultimately, a total of 54 articles were chosen. Despite the effective utilization of AI technologies in the healthcare sector for many decades, various explicit and implicit obstacles remain, obstructing additional integration.

This literature review has identified obstacles across four primary domains: operational, technological, security and ethical. By identifying and understanding the obstacles that hinder the effective integration of AI in healthcare, leaders in the field will be more prepared to tackle these issues and adopt reliable AI technologies to improve patient care and the healthcare system as a whole. Therefore, it is essential to advance comprehensive and well-informed HTAs in the appraisal of AI systems to guarantee transparency and thoroughness of healthcare systems.

Keywords: Artificial Intelligence; Health Economics; Cost-Effectiveness; Personalized Care; Hospital Efficiency; Barriers to Implementation; Health Technology Assessment

Abbreviations: AI: Artificial Intelligence; CBA: Cost-Benefit Analysis; CEA: Cost-Effectiveness Analysis; CUA: Cost-Utility Analysis; DL: Deep Learning; EHR: Electronic Health Record; HEOR: Health Economics and Outcomes Research; ICER: Incremental Cost-Effectiveness Ratio; ML: Machine Learning; NLP: Natural Language Processing; QALY: Quality-Adjusted Life Year; HTA: Health Technology Assessment; HTAs: Health Technology Assessments; MeSH: Medical Subject Headings; PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses; QALYs: Quality-Adjusted Life Years; ORS: Operating Rooms; AUC: Area Under The Curve; EHRs: Electronic Health Records; IoMT: Internet of Medical Things; AIoT: Artificial Intelligence of Things; LLMs: Large Language Models; IoT: Internet of Things

Introduction

Healthcare spending is increasing globally at an unsustainable rate. A variety of factors, such as changes in population demographics, increased life expectancy, the rising incidence of chronic health issues, the advancement of modern healthcare services, and the rapid rise in healthcare costs driven by high inflation and increasing pension responsibilities, have together exacerbated the financial pressure on healthcare systems. The COVID-19 pandemic has underscored the significance of public policy concerning health. Countries need to depend on thoughtfully structured and efficient health care systems, along with policies grounded in evidence, to mitigate the transmission of viruses and address any forthcoming challenges. Furthermore, public policy will remain pivotal in tackling future health issues. Ultimately, it is recognized that the healthcare sector is among the particular sectors that necessitates the incorporation of sophisticated methodologies and research processes to ensure the efficient delivery of services. In this context, health economics is responsible for tackling complex issues related to the cost and value of healthcare interventions. This includes evaluating the efficiency and effectiveness of treatments, examining disparities in access to healthcare, utilization, and outcomes. Additionally, it involves analyzing the economic burden of diseases and assessing how economic tools—such as incentives for behavioral change-can help alleviate inequities and support evidence-based decision-making regarding resource allocation [1-6].

Through the utilization of its capacity to process extensive datasets, recognize trends, and generate forecasts, Artificial Intelligence (AI) technologies have become pervasive. They encompass a variety of computational methods that empower machines to execute tasks usually requiring human intelligence, thereby addressing challenges related to health economics and markedly enhancing the precision, efficiency, and customization of health economics evaluations. These methodologies include, but are not limited to, machine learning (ML), deep learning (DL), and natural language processing (NLP) approaches that have been widely applied in the healthcare sector for purposes such as predictive analytics, diagnostic support, and personalized treatment planning tailored to individual requirements. Additionally, generative AI, which involves models capable of producing original content based on collected data, is acknowledged as a significant asset in various clinical environments. Nonetheless, while the clinical benefits of AI in healthcare are broadly recognized, the economic implications remain less distinctly articulated [7-15]. Health Technology Assessment (HTA) represents a structured methodology for assessing the clinical, economic, and societal impacts of health technologies, including AI-driven medical devices. The incorporation of Health Technology Assessment (HTA) into healthcare systems facilitates evidence-based approaches, offering essential insights and constructive feedback. This ensures that resources allocated appropriately, technologies implemented efficiently, and care delivery is in harmony with broader performance goals.

Significantly, the role of HTA is especially apparent in budgeting procedures, investment strategies, and the oversight of technology lifecycles, which includes planning for obsolescence and management control. Furthermore, it is essential for policymakers and healthcare executives, providing a structure that shapes policies aimed at optimizing the utilization of existing health resources prior to their application in clinical environments [16-19]. Nonetheless, in spite of the increasing enthusiasm, the actual economic effects of AI-driven tools are not consistently recorded, as studies frequently vary in their methodologies, scopes, and geographic areas of focus. This absence of thorough data creates obstacles for those aiming to make well-informed choices regarding the adoption and investment in AI technologies. Consequently, the objective of the present systematic review was to rectify this gap to harness AI tools that can enhance the fundamental functions of contemporary formal health technology assessments (HTAs) pertaining to AI applications in healthcare, scrutinizing their methodologies, results, and identified challenges [20-23]. In order to fulfill this objective, the article structured as follows: the next section delineates the methodologies employed to carry out the scoping review; the third section presents and elaborates on the findings; the fourth section includes a discussion that encompasses the formulation of a framework integrating Health Technology Assessments (HTAs). Lastly, the concluding section summarizes the key points.

Methods

This scoping review aims to map the existing literature on the health economic implications of AI within healthcare settings, focusing on how these technologies influence performance management, cost-effectiveness, and patient outcomes. With the aim of generating evidence and conclusions on the (long-term) implications for supporting AI technologies, their implementation and funding decisions aimed at improving outcomes in healthcare settings, through informed HTAs. A thorough investigation performed across six electronic databases: PubMed/Medline, Scopus, Embase, Web of Science, EconLit, and Google Scholar (see Table 1). The search methodology integrated terms associated with AI, healthcare, and economic assessments utilizing Boolean operators (AND/OR) and Medical Subject Headings (MeSH) as appropriate. To conduct this systematic review, the researchers adhered to the 2020 Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure methodological rigor and transparency. As such, the researchers followed a five-stage process: identifying relevant studies, selecting studies, mapping data, synthesizing, and presenting results. The literature search resulted in 532 investigations, sourced from the Pubmed, Scopus, Cinah, Embase, Web of Science, EconLit, and Google Scholar databases. The information specialist within the research team exported the findings to Zotero and eliminated duplicates, ultimately retaining 486 articles.

 DOI: 10.26717/BJSTR.2025.64.009977

Table 1: Search Strings for Databases.

Database	Search String
PubMed/Medline	("Artificial Intelligence"[Mesh] OR "Machine Learning"[Mesh]) AND ("Cost-Benefit Analysis"[Mesh] OR "Economics, Medical"[Mesh]) AND ("Healthcare"[Mesh] OR "Delivery of Health Care"[Mesh]) AND ("Health technology assessment"[Mesh] OR "HTA"[Mesh])
Scopus	TITLE-ABS-KEY(("artificial intelligence" OR "machine learning") AND ("cost savings" OR "cost-effectiveness") AND ("healthcare" OR "health system"))
Embase	('artificial intelligence'/exp OR 'machine learning'/exp) AND ('cost benefit analysis'/exp OR 'health economics'/exp) AND ('health care'/exp OR 'health care system'/exp)
Web of Science	TS= ("artificial intelligence" OR "AI" OR "machine learning") AND TS= ("cost analysis" OR "economic evaluation") AND TS= ("healthcare" OR "hospital")
EconLit	SU w("Artificial Intelligence" OR "Machine Learning") AND SU ("Health Economics" OR "Cost-Benefit") AND SU ("Healthcare Systems")
Google Scholar	TS= ("artificial intelligence" OR "AI" OR "machine learning") AND TS= ("cost analysis" OR "economic evaluation") AND TS= ("healthcare" OR "hospital") AND ("Health technology assessment"[Mesh] OR "HTA"[Mesh])

Following a pilot test, titles and abstracts assessed by two researchers to ascertain their relevance to the study's objectives, focusing on English-language studies with broadly applicable contributions. Consequently, 69 articles retained, with 417 recovered (see Figure 1). The same reviewers meticulously examined the full texts of the selected citations, making decisions based on their alignment with the study's objectives. After this thorough review, 16 articles excluded because of the full text evaluation, leading to the inclusion of 54 articles in the qualitative synthesis [22-24].

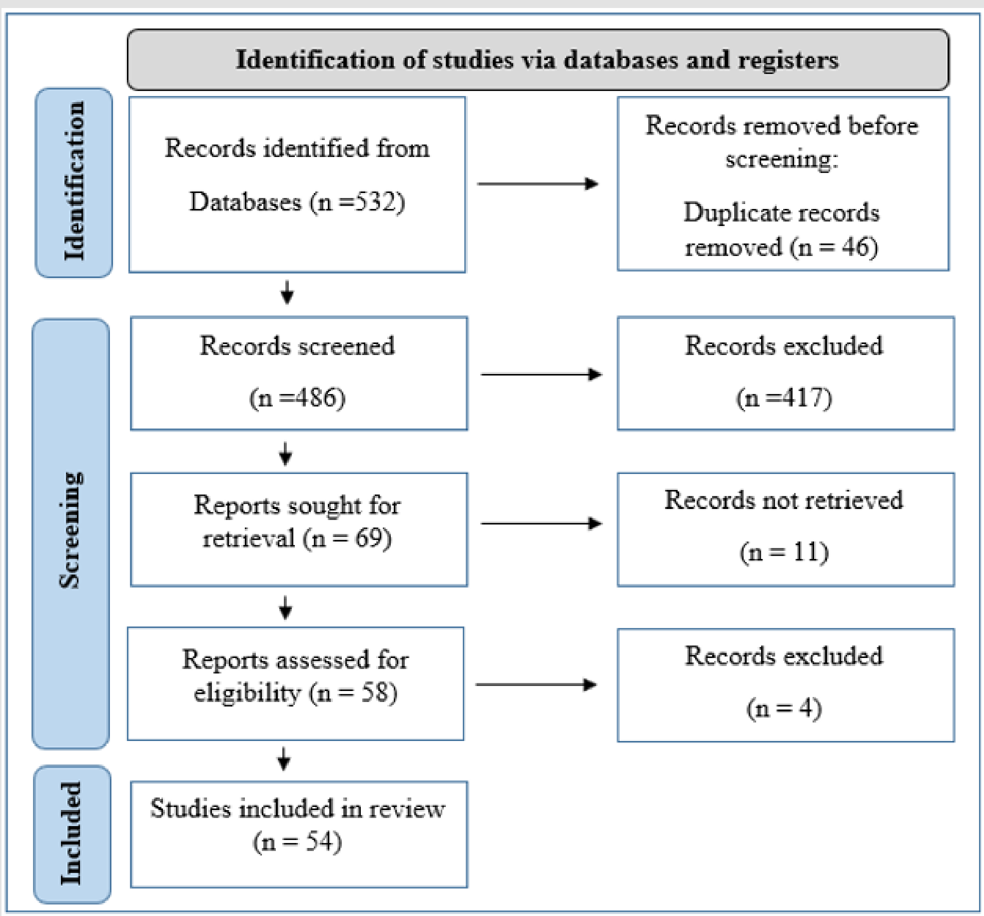

Figure 1: PRISMA flow diagram of article identification, exclusion, and number included for qualitative synthesis.

Results

Assessing the deployment of new technologies, particularly within the healthcare industry, poses considerable difficulties and inevitably influences financial outcomes, either directly or indirectly. Furthermore, any evaluation must include the implications that the implementation of the new technology has on all stakeholders, in this case, healthcare facilities, providers, patients, taxpayers and the state. In this context, as AI technology can serve a variety of purposes, it is necessary to continuously investigate the impact of AI on healthcare economics under specific criteria.

How Artificial Intelligence is Impacting Healthcare Economics

Artificial Intelligence (AI) and Machine Learning (ML) significantly influence Health Economics and Outcomes Research (HEOR) by providing powerful instruments for the analysis of large datasets, improving the precision of predictive analytics, and optimizing healthcare delivery. Although the initial investment required for the adoption of AI is considerable, the anticipated long-term savings and advantages are likely to be considerable. Until now, AI is being applied across various domains of health economics, including:

Cost-Reduction and Savings: AI-enabled technologies hold promises for cost savings for both healthcare systems and patients. Telemedicine and remote patient monitoring technologies possess the capacity to diminish both initial hospitalizations and subsequent readmissions through continuous surveillance of patient health status and the provision of timely notifications to healthcare practitioners when clinical deterioration is detected, thereby enabling early intervention prior to the exacerbation of medical conditions. A research study assessing different trial strategies for the initial treatment of metastatic colorectal cancer revealed that an AI-driven approach, led to considerable cost reductions. This study illustrated AI's capability to customize patient care more effectively, achieving at least a 25% decrease in hospital admissions and an impressive 90% decrease in hospital discharges. A subsequent investigation into the convergence of AI and telehealth applications within ophthalmological practice demonstrated that the synthesis of these technological modalities can yield substantial economic benefits. Through comprehensive analysis of 5,456 ocular examination encounters, researchers determined that approximately 15% of emergent patient transfers and 24% of remote specialist consultations demonstrated appropriateness for telemedicine implementation, ultimately generating an estimated cost reduction of $1.1 million. Substantial economic benefits spanning various healthcare sectors are realized by minimizing unnecessary procedures and through the reduction of redundant or superfluous diagnostic procedures.

Furthermore, preventive healthcare provided by primary care, when augmented by AI, significantly influences medical expenses by facilitating early disease detection and timely interventions. This proactive strategy effectively reduces the need for hospital admissions and costly interventions. A notable instance is the use of advanced AI technologies that are capable of detecting illnesses in their initial stages, thereby facilitating timely and efficient treatments that result in shorter hospitalizations. A reduced utilization of health resources inherently leads to lower expenses for both healthcare providers and patients. All these benefits, suggest a remarkable economic return over time, yielding enduring positive impacts on the entire healthcare ecosystem [25-32].

Cost-Effectiveness: Besides cost savings, AI possesses the capability to evaluate extensive datasets concerning treatment outcomes and associated costs, thereby pinpointing the most economically efficient interventions. Generally, methodologies such as cost-effectiveness analysis (CEA), cost-utility analysis (CUA), and cost-benefit analysis (CBA) are crucial for determining if the incorporation of AI is warranted in light of its related expenses. These analytical methods compare the incremental expenses incurred by the adoption of new technologies with their incremental advantages, frequently quantified in terms of quality-adjusted life years (QALYs). Another critical metric is the incremental cost-effectiveness ratio (ICER) which evaluating the efficiency of healthcare interventions and resource allocation strategies. In their study, Rossi, et al. [30]) conducted an analysis examining the economic efficiency of AI-driven clinical decision support technologies in the identification of melanoma, dental caries, and diabetic retinopathy, finding that the implementation of such AI-powered diagnostic tools resulted in healthcare facility expenditure decreases ranging from 15% to 20%. Moreover, Hill, et al. [31]) employed QALY projections across patient lifetimes, predicting outcomes based on the mitigation of stroke and atrial fibrillation risks. Their findings demonstrated that a machine learning-driven risk assessment model yielded incremental cost-effectiveness ratios between £4,847 and £5,544 per QALY obtained.

These figures indicate a significant decrease in relation to the National Health Service's cost-effectiveness benchmark of £20,000 per QALY, accomplished by the algorithm's ability to enhance screening intervals and minimize superfluous procedures. In another study, Areia, et al. [33]) demonstrated that AI-enhanced polyp identification in colorectal cancer screening programs yields superior clinical results and exhibits favorable cost-effectiveness profiles, indicating that these technological advances have the potential to decrease both the occurrence and death rates associated with colorectal cancer while warranting their upfront costs through sustained economic benefits over time [31,33-36].

Allocation of Resources and Operational Efficiency: Numerous research studies indicate that healthcare interventions utilizing AI enhance the allocation of resources, thereby guaranteeing that investments produce maximum returns in relation to enhanced health outcomes and economic productivity. In hospitals, operating rooms (ORs) represent one of the most vital resources. As such,

DOI: 10.26717/BJSTR.2025.64.009977

hospitals cost savings primarily arise from initiatives that enhance clinical operations, including the optimization of operating rooms, the elevation of care quality, and the enhancement of safety measures, such as the management of patient deterioration and the detection of adverse events. According to Yagi, et al. [37]), machine-learning algorithms possess the potential to support surgical decision-making processes by facilitating optimal patient selection and enhancing operational efficiency within surgical workflows. Such technological interventions may consequently result in the mitigation of superfluous medical procedures while simultaneously optimizing the allocation of healthcare institutional resources and their organizational readiness. Although these technological applications remain in their nascent stages of development, preliminary empirical investigations indicate measurable advantages with respect to both economic efficiency and enhanced clinical outcomes for patients. Conversely, inefficient operational practices can result in significant time wastage, leading to excessive spatial requirements, obstructing patient access, diminishing the patient experience, and adversely affecting the financial performance of hospitals.

Predictive analytics models have already shown remarkable performance metrics, including high area under the curve (AUC) values, when applied in diverse hospital management applications like resource utilization forecasting and patient flow optimization [11,12,27,38-42]. Other statistical evidence suggests that AI enhances supply chain management within the healthcare sector by forecasting the demand for medical supplies and pharmaceuticals through the utilization of sophisticated machine learning models. These models scrutinize a broad array of data sources, which encompass historical consumption trends, seasonal variations, and real-time data regarding disease outbreaks. By amalgamating various datasets, AI is capable of accurately predicting future supply requirements for healthcare providers, thereby augmenting the efficiency and reliability of the supply chain. AI can also group similar data points based on parameters such as consumption rates and seasonal demand fluctuations. In the context of healthcare, clustering can be employed to categorize supplies according to their usage trends, facilitating the identification of supplies that are consistently required as opposed to those that exhibit greater variability [43,44].

Patient Outcomes: AI is enhancing telemedicine platforms by providing sophisticated diagnostic and advisory services, which enable healthcare professionals to assess patients remotely and tailor virtual advisory services according to individual patient data. AI-powered chatbots and virtual assistants enhance patient engagement by providing support and streamlining the appointment scheduling process. Additionally, the role of AI in remote patient monitoring and predictive analytics promotes preventive care for chronic conditions and foresees possible health issues. More than ever, at-risk populations (e.g., cancer, kidney, heart patients etc.) and individuals residing in rural or island regions have gained greater accessibility and knowledge about their health. Similarly, within the framework of hospital organizational functionality, AI through the automation of repetitive healthcare tasks, thereby alleviating workload. This decrease in workload lessens toxicity and allows healthcare professionals to dedicate additional time to complex, value-enhancing tasks, thereby enhancing the services provided and strengthening the physician-patient relationship [10,13,14,45,46].

Restructure, Scalability and Continuous Improvement of Organization: The paradigm shift towards outcome-oriented healthcare delivery models is experiencing accelerated adoption worldwide, as governmental authorities and healthcare financing entities endeavor to synchronize economic motivations with clinical efficacy measures and fiscal optimization strategies. AI can be used to optimize the structure and parameters of a model, as the application of computational algorithms and models (ML/DL/NLP), can be used to analyze large-scale datasets (e.g. electronic health records), complex medical data or images, support clinical decision-making, and automate administrative or diagnostic tasks to improve the diagnostic accuracy compared to manual screening and speed of health economic models by categorizing data, capturing complex relationships within the data, and optimizing model parameters. They can additionally serve to pinpoint the key elements that influence the efficacy and expense of a healthcare intervention, as well as to enhance the prioritization of these elements within the ultimate model. The latter can result in a decreased likelihood of misdiagnosis, since a decrease in diagnostic errors leads to reduced costs associated with unnecessary or ineffective treatments. In addition, it leads to a reduction in follow-up costs; for instance, AI-assisted X-ray analysis can minimize the necessity for follow-up appointments and repeated imaging but also enable prioritization of urgent cases. A research investigation demonstrated that the implementation of AI algorithms for real-time patient data analysis resulted in substantial reductions in emergency department utilization and hospital readmission frequencies. Of particular significance, the requirement for expensive domiciliary healthcare visits decreased by a minimum of 22% [7,11,47-51].

Enhancing Labor Productivity: Improving labor productivity is an essential element in the healthcare sector. Historically, the increase in labor productivity in healthcare has experienced a decline. For many healthcare organizations, labor represents the largest variable-cost factor. Healthcare settings experience substantial financial burden attributable to administrative inefficiencies, with empirical evidence suggesting that the absence of automated systems contributes to approximately 15-30% of aggregate healthcare expenditures. Research indicates that the implementation of AI technologies has the potential to automate administrative tasks and diminish manual labor requirements in prior authorization procedures by 50-75%, thereby enabling healthcare organizations to reallocate human capital toward direct patient care delivery and clinical services. Nevertheless, value can also be generated through nonfinancial means. For instance, supplying clinicians with data at the time of service could improve the treatment choices made for patients, informed by clinical evidence. Consequently, health outcomes may be enhanced without an increase-or potentially a decrease-in costs [25,52-55].

Enhanced Decision Making: AI technologies in the healthcare sector demonstrate the capacity to furnish clinicians and care teams with actionable insights derived from intricate and diverse data sources. For example, AI-driven systems facilitate the continuous monitoring of patients by employing wearable devices and sensors that gather real-time vital sign data. This capability enables healthcare providers to receive immediate alerts concerning any identified abnormalities and to intervene promptly, which is especially beneficial for the management of chronic conditions. Furthermore, AI models can swiftly analyze substantial amounts of electronic health records (EHRs), laboratory results, imaging data, and even unstructured clinical notes to uncover patterns that may not be readily visible to human practitioners. By utilizing advanced analytics to integrate patient information, clinical guidelines, and real-time data streams, diagnostic accuracy, risk stratification, and treatment planning are enhanced, thereby improving both the speed and precision of medical decision-making. These enhanced efficiencies are particularly significant in acute care environments, where timely intervention is crucial for patient outcomes. The lack of contemporaneous data streams and forecasting functionalities compels numerous healthcare institutions to adopt reactive operational paradigms instead of anticipatory approaches, consequently generating systemic inefficiencies and temporal impediments in medical service delivery [56-58].

Personalized Healthcare: The integration of AI with Internet of Medical Things (IoMT) technologies, commonly known as the Artificial Intelligence of Things (AIoT), has enabled continuous patient monitoring and real-time data transfer across various healthcare environments. Therefore, personalized healthcare based on AI has shown its ability to exploit data and tailor treatments according to individual patient requirements. This includes reducing unnecessary expenses, minimizes recall appointments, improving compliance measures, and minimizing malpractice incidents. Furthermore, the incorporation of Large Language Models (LLMs) into clinical workflows promotes a transition towards personalized medicine by utilizing genetic profiles obtained from patients' medical histories, thus enhancing outcomes and fostering a more patient-centered approach to care. This is particularly beneficial in oncology, as it helps to identify the most effective chemotherapy treatments while reducing side effects. Such integration improves access to high-quality healthcare, providing sustainable advantages at scale across various populations, and addressing regulatory challenges that impede the safe and effective deployment of AI in the healthcare industry. Additionally, AI holds the promise of revolutionizing population health management by forecasting health trajectories and improving community health outcomes. This can help identify populations at risk (e.g., by spotting issues like hospital-acquired infections or medication errors early), implement preventive measures, and improve overall community health outcomes.

Obviously, a healthier population fosters a more efficient workforce, promoting economic development and decreasing public expenditure on medical services, thus contributing to reducing transaction costs, fewer complications and improving the efficiency of services [31,59-63]. Table 2 comprehensively illustrates the methods in which AI is transforming performance management, promote effectiveness, improving patient outcomes, and promoting positive economic effects for healthcare systems.

Table 2: How AI Abilities are transforming healthcare Systems.

AI Abilities	Used Methodologies	Performance Management	Effectiveness	Patient Outcomes	Economic Consequences
predicting health trajectories	statistical modeling and machine learning	proactive interventions	identify risk factors and potential health developments	future health outcomes with customizing treatment plans	indirectly and future
recommending treatments	based on an assessment of the patient's condition, preferences, and possible reactions to various treatments	reduced misdiagnosis	enhanced effectiveness of treatment plan through patient engagement and adherence	customized recommendations	directly through lower treatment costs
guiding surgical care	a comprehensive framework that includes preoperative assessment based on a complete patient examination history and by adhering to established protocols and guidelines	healthcare providers are capable of adeptly maneuvering through the intricacies of surgical procedures	enhanced precision in surgeries, rehabilitation and quality of care delivered	ensured patient safety	directly through the best results and unwanted repetitions or side effects

 DOI: 10.26717/BJSTR.2025.64.009977

monitoring patients	systematic observation and assessment of individuals' health status	allows prompt intervention and management, also plays a vital role in chronic disease management	ensures timely detection of any changes in a patient's condition	continuous supervision, necessary to maintain optimal health and prevent complications	directly through lower treatment costs
supporting population health management	systematic collection and analysis of health data	fosters better individual health but also contributes to the overall efficiency of healthcare systems	promote preventive care, enhance access to services, and ultimately reduce health disparities	improving patient engagement	optimizing resource allocation
recording digital clinical notes	by the integration of digital notes into electronic health records	facilitating accurate documentation and efficient communication among medical professionals	healthcare providers can streamline their workflows, reduce the risk of errors associated with handwritten notes, and ensure that critical data is readily available for clinical decision-making	supports better data analysis and research, ultimately contributing to improved patient outcomes	directly through lower treatment costs
optimizing operational processes	through the analysis and refinement of workflows, resource allocation, and communication channels	processes remain agile and responsive to changing demands	continuous improvement is facilitated	faster and updated services	reduced costs and increased productivity
readiness for change	systematic observation of health data and changes	preparedness to embrace and adapt to new circumstances or transformations	improved outcomes and sustained progress	greater adaptation to the needs of patients, especially during disasters or epidemics	optimizing resource allocation

The Implementation Costs and Uncertainties Surrounding Ai in Healthcare Systems

Although the incorporation of AI-driven tools into healthcare systems is widely accepted and acknowledged for its potential to significantly reduce costs and provide undeniable benefits; however, the major roadblock in its widespread adoption requires considerable investment in technological and digital infrastructure, data management and access that must be critically examined [62].

The Role of Technological Infrastructure: Typical assessments of expected returns and cost-benefit analyses for significant investments in emerging technologies, particularly in AI, rely on developmental determinations that often result from largely subjective or dialogical discussions. However, even when business justifications are made, there is insufficient oversight of whether the expected benefits have been realized after deployment. This deficiency stems from established contracts and historical patterns of non-performance, combined with management's acceptance of practices where attention shifts to subsequent initiatives after acquisition processes have been completed. An additional pertinent issue that emerges is the ongoing necessity for technological enhancement and upgrades throughout the procurement process. Given that this requirement is not incorporated into the bidding process, providers frequently lack the motivation to include it, as doing so would be disadvantageous to them. Until recently, AI was primarily regarded in the context of futuristic applications, particularly in the development of robots designed to replicate human capabilities. However, healthcare organizations are now beginning to recognize the value of more pragmatic applications, including real-time data gathering and informed decision-making. Healthcare providers frequently find themselves equipped with obsolete technology, which poses significant challenges for AI applications that are perpetually advancing and require regular updates to enhance their performance.

For instance, Internet of Things (IoT) devices demand stable internet connectivity and reliable power sources. In regions where this infrastructure is inadequate or inconsistent, investments in AI may not yield the anticipated improvements in care delivery or cost-effectiveness. As a result, such investments could result in technology that remains underutilized and resources that are wasted. Major deficiencies in technological infrastructure can exacerbate existing health disparities instead of alleviating them [62,64-70].

Computational Resources and Cloud-Based Services: AI algorithms, especially those that utilize deep learning and neural networks, demand considerable computing power, particularly during the development and training stages. Healthcare organizations ought to assess their current computing resources, including servers, GPUs, or TPUs, along with their cloud computing capabilities, to ascertain whether these are adequate for AI workloads or if further investments in hardware or cloud services are warranted. A significant concern noted is the restricted lifecycle management linked to on-premises hardware. As technology progresses, the necessity to upgrade and replace hardware emerges, resulting in increased costs over time. [67-70]. At the same time, healthcare supply chain management, along with the ERP system and item master, acts as the backbone for AI-enabled automation and a trusted source of information about medical supplies and the workflows that guide procurement activities by providing continuous updates. This lays the foundation for cloud-based procurement operations, which can lead healthcare organizations to boost operational and cost efficiency, reducing errors and operational costs while equipping procurement organizations with analytics for further optimizing logistics. Healthcare providers and medical equipment suppliers try to strengthening this foundation by integrating additional cloud-based automation and solutions that improve supply chain efficiency [44,71-73].

Workforce Training: A thorough comprehension of the abilities and functions of AI technologies in the healthcare field is still at an early stage, requiring significant education and training in AI. The diverse degrees of technological proficiency, contentment with, and comprehension of the current technology must be addressed before the workforce, which will be essential for utilizing this technology, can feel at ease or skilled in clinical settings. Currently, a multitude of studies suggests that healthcare practitioners possess minimal to no training in assessing AI software. Additionally, the majority of the evidence concerning the application of AI in healthcare is retrospective, revealing a considerable deficiency of randomized controlled trials for clinicians to assess. Regrettably, frustrations may intensify as physicians attempt to integrate AI platforms while concurrently grappling with existing healthcare technologies. If these technologies have not been subjected to thorough evaluation before their deployment and application, it is probable that this will result in significant harm to patients, a persistent erosion of trust in the medical field, and erroneous interpretations at the population level. Healthcare providers must develop training initiatives specifically tailored for clinicians who are obligated to employ AI systems, intended to tackle the diverse challenges that emerge from unfamiliar technology [21,74-77].

Other Issues Connected with Transaction Costs: AI systems depends on heaps of good-quality health data to learn and generate precise predictions. Furthermore, the potential for privacy violations arising from the misuse or reidentification of pseudo-anonymized data presents a considerable issue. Sophisticated methods may be capable of reversing the anonymization process, thereby jeopardizing patient confidentiality. As such, gathering, sanitizing, annotation and managing healthcare data can be quite expensive and time-consuming, particularly when the data is dispersed. The intricacies involved in data management, along with the stringent security measures necessary (e.g., cybersecurity measures, encryption, and strict access controls) for its maintenance or transfer, may result in elevated transaction expenses, which could undermine anticipated savings if not handled properly. Moreover, these factors can significantly erode public trust and diminish societal benefits if the forecasts or outcomes generated are biased, detrimental, or merely ineffective. It is imperative for AI system design teams to consider these aspects, even when confronted with pressing demands for innovation or cost efficiency. Regulatory frameworks must consequently adapt to include ongoing monitoring, new classifications for advanced models, and a clear emphasis on ethics, fairness, non-discrimination, and the respect for patient autonomy [64,78-80].

The Significance of Informed Health Technology Assessment (HTA) in The Evaluation of Emerging Ai Systems

It is important to highlight that, before entering clinical development; Digital technologies typically undergo thorough validation procedures to confirm that their performance meets the necessary standards. However, the operational performance of digital models can deteriorate throughout the development phase due to environmental modifications to their operational context. Furthermore, correlation-based methodologies can demonstrate strong internal validity, demonstrating optimal performance when the target demographic closely resembles the training data set. The swift progress in fields such as precision medicine, gene therapy, and digital health solutions indicates that the extensive implementation of AI or the modification of current AI frameworks will require significant reorganization of IT infrastructures. This restructuring will have resource implications, complicating the search for sufficient investment in the face of competing needs for healthcare equipment. Additionally, there is a risk that ineffective AI solutions may be adopted due to insufficient and limited evidence. Both of these situations could lead to potential health risks and unnecessary costs, and it is likely that these challenges will persist until AI, with its seemingly limitless potential, is recognized as an intervention that necessitates comprehensive assessment. Utilizing HTA is strategically advantageous during the initial phases of technology development.

Early HTA enables stakeholders to anticipate clinical outcomes and cost-effectiveness prior to complete market introduction, thus aiding in investment choices, directing research priorities, and enhancing budget distribution. This methodology is especially significant for innovations that are high-risk or high-cost, as uncertainty may hinder their adoption [81-83]. Considering the significant financial resources required to further integration of AI into healthcare environments, evaluating its economic feasibility is crucial, leading to a marked increase in the demand for thorough HTA assessments. The critical role of the HTA in the introduction, scaling and expansion of AI systems, must be separated in three different domains, such as [17,18,82,84-86].

DOI: 10.26717/BJSTR.2025.64.009977

Organizational and Economical Domains

Requires Organizational Readiness and Workflow Integration

An AI-powered device may be technically sound but fail if it doesn't integrate smoothly into clinical workflows. HTA assesses the organizational and human factors involved in implementing a new technology, ensuring developers consider training, resource allocation, and ease of use in their design.

Focuses on Value for Money: The economic component of HTA moves the conversation beyond just the technology's performance to its overall value. It analyzes factors such as cost-effectiveness, long-term costs, and economic benefits, which encourages AI developers to build solutions that not only work but are also efficient and sustainable.

Technical and Performance Domains

Encourages Data Quality and Integration

AI models trained on poor-quality or fragmented data will perform poorly. The HTA process forces a critical evaluation of data quality and the device's ability to integrate with different healthcare data sources, pushing developers to improve their data infrastructure and management.

Promotes Continuous Monitoring and Reassessment

an AI system can evolve over time based on the data it processes. HTA and regulatory bodies must develop guidelines that mandate continuous monitoring and reassessment of AI performance, ensuring the technology remains safe and effective as it adapts.

Requires Robust Clinical Validation: Traditional HTA standards require rigorous clinical validation of medical devices. By implementing these standards in AI, developers are compelled to demonstrate the accuracy, sensitivity, and specificity of their products in practical environments and among varied patient demographics. This procedure aids in recognizing and rectifying performance problems and biases.

Ethical and Social domains

Addresses Algorithmic Bias

AI can reflect biases present in its training data, which may lead to unequal treatment for certain patient groups. The HTA framework specifically examines issues of fairness and bias, pushing developers to mitigate these issues and ensure their AI models promote equitable access to care.

Drives Transparency and Explainability

The vast majority of algorithms suffer from a deficiency in interpretability or transparency, leading to a situation where developers are either unable or unwilling to clarify the rationale behind their decision-making processes, a phenomenon commonly referred to as the "black box effect", making it difficult for users to understand how they arrive at a decision. HTA encourages the explainability and transparency of AI systems. Forcing developers to disclose how their algorithms work builds trust and enables healthcare professionals to understand and challenge the AI's recommendations.

Enforces Accountability and Clear Liability

When an error or adverse event occurs with an AI-based device, determining liability can be complex. The HTA framework prompts an examination of legal frameworks and liability guidelines, which clarifies responsibility and pushes for robust safety measures. By holding AI systems to these standards, the HTA process acts as a quality assurance mechanism. It provides a structured evaluation that forces developers to confront and address the real-world implications of their technology, resulting in more refined, responsible, and effective AI solutions for healthcare.

Conclusion

Healthcare systems represent a multifaceted and demanding environment; nonetheless, AI systems have proven effective in forecasting which treatment protocols are most probable to result in favorable outcomes, taking into account the specific context of the treatment setting and the distinct attributes of patients. Furthermore, AI holds significant promise in tackling global health challenges by enhancing disease surveillance, optimizing resource allocation in resource-limited settings, and promoting the development of affordable and accessible healthcare interventions. Evaluating AI implementation in health economics means systematically measuring costs, economic value, and health outcomes linked to AI, while considering operational impacts and methodological nuances of AI technologies. This enables healthcare decision-makers to understand whether AI delivers tangible economic benefits and under what conditions. Regrettably, innovative digital technologies, particularly those utilizing AI, encounter further obstacles to their adoption. Although they hold great potential for enhancing clinical decision-making and operational efficiency, these tools frequently find it challenging to progress from mere performance metrics to tangible clinical utility. Numerous AI-driven solutions do not possess the longitudinal or real-world evidence required for formal HTA, and existing regulatory frameworks have yet to be completely tailored to accommodate their distinct life cycles and risk characteristics.

Therefore, tackling issues associated with infrastructure, data integrity and security, interoperability, and ethical considerations is essential for guaranteeing the responsible and fair deployment of AI within healthcare systems.

Funding

This research was not funded or supported by any organizations.

Acknowledgment

Not applicable.

Competing Interests

The authors declare no competing interests.

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ISSN: 2574-1241

DOI: 10.26717/BJSTR.2025.64.009977

Dimitrios Karaferis. Biomed J Sci & Tech Res