The Impact of Artificial Intelligence on the Health Economy, Workforce Productivity, and Administrative Efficiency: A Systematic Review

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ABSTRACT

Background:
Healthcare systems globally are under increasing financial and operational strain due to aging populations, rising expenditures, and workforce shortages. Amid these challenges, artificial intelligence (AI) has emerged as a promising tool to enhance system-level performance, particularly in cost reduction, productivity gains, and administrative efficiency.

Objective:
This review aims to synthesize existing evidence on the macro and system-level impact of AI implementation across three key domains: the health economy, workforce productivity, and administrative efficiency.

Methods:
A systematic review methodology was employed, allowing for the integration of diverse data sources and study types. Literature was systematically identified through PubMed and Google, covering publications from 2020 to July 2025. Studies were included if they evaluated AI's impact on national or regional health expenditure, labor restructuring, or process efficiency. Thematic synthesis was guided by a conceptual framework modeling AI as a system-wide catalyst.

Results:
Twenty-four studies were included. AI implementation demonstrated potential cost savings of 5–10% in national health expenditures, driven by automation in hospital operations and administrative processes. AI-supported interventions reduced diagnostic time by up to 90% and treatment costs by over 30% in specific applications, such as cancer diagnosis and radiotherapy. Administrative tools, including AI-assisted documentation and claims processing, achieved efficiency gains of up to 40%. However, reliance on simulated models, short-term studies, and single-center data limits generalizability.

Conclusions:
AI presents significant potential to enhance health system efficiency and reduce costs. Real-world implementation studies, standardized outcome metrics, and robust governance frameworks are essential to validate these gains and ensure equitable, sustainable adoption.

INTRODUCTION

Health systems around the world are facing growing pressure. Spending on healthcare is rising faster than many economies can keep up with due to rapid aging population[1]. The percentage of GDP spent on health has shown a significant increase over the past decades. According to projections, healthcare spending in the United States is expected to grow faster that the GDP, reaching 19.7% of GDP by 2032, up from 17.3% in 2022[2]. This trend reflects a broader global pattern where health spending as a share of GDP has been increasing, driven by factors such as economic development, demographic changes, and policy shifts. For instance, global health spending was 8.6% of the global economy in 2016 and is projected to reach 9.4% by 2050 [3].

The escalating cost occurs while many health systems struggling with insufficient healthcare funding from both the public and private sector. For example, the UK's National Health Service (NHS) faces a projects £ 4.8 bill shortfall in its 2024/2025 revenue budget, raising concerns about potential service cuts without additional funding [4]. In the United States, proposed federal cuts of $ 880 to Medicaid over the next decade threaten to reduce access to essential services cater for vulnerable populations [5].

Additionally, many health system has shortages in the healthcare workforce, making it challenging to meet the growing demand[6]. This issue is compounded by the maldistribution of healthcare professional across geographical area, leading to inequalities in service provision in underserved and remote areas. Adding to this burden is the increasing amount of administrative work that clinicians and managers face growing administrative burden, diverting valuable time from direct patient care. According to a time and motion study, physicians in ambulatory practice spend 49.2% of their time on electronic health record (EHR) and desk work and 27.0% on direct clinical face time with patients during office hours[7]. Another study in the Journal of General Internal Medicine found that physicians spend 20.7% of their time on EHR input alone and 7.7% on administrative activities, with 66.5% of their time on direct patient care (including multitasking with EHR) [8].

Against this backdrop, Artificial Intelligence (AI) and Machine Learning (ML) have captured attention as tools that could potentially reshape how health systems function. AI is not new—it began with early attempts to simulate human thinking using symbolic systems and rule-based expert programs in the 1980s. These tools could be useful in narrow areas but were limited by their inability to handle complexity and real-world uncertainty. What has changed in recent years is the rise of new forms of AI, particularly deep learning and large-scale foundation models. These systems learn from enormous amounts of data and can now perform tasks that once required human intelligence—such as reading radiology scans, understanding natural language, writing computer code, or even engaging in meaningful conversation. Tools like GPT and Gemini represent a leap forward not only in accuracy but also in general intelligence. In healthcare, they are already being tested for clinical decision support, predictive risk modelling, and automating administrative tasks. At present, AI tools have been increasingly used and accepted in clinical practice, particularly in imaging and diagnosis. LLMs have also been used for documentation, administrative, or coding work in clinical settings [9,10].

But alongside this rapid progress, concerns remain. These systems rely heavily on the data used to train them—data that may be incomplete, biased, or not representative. AI decisions can also be difficult to interpret or explain, which raises issues of trust, accountability, and ethics [11]. While much attention has focused on AI's technical capabilities, its broader impact on health systems as a whole requires deeper investigation. From a policy prospective, it is essential to examine the macro-level impact of AI on health economy. This study reviews the current evidence on how AI is influencing three key areas: (1) overall health spending and cost control, (2) administrative efficiency, and (3) workforce productivity.

RESULTS

Summary of Included Studies

This review includes 24 studies examining the macro-level impact of artificial intelligence (AI) across three key domains: health economy, workforce productivity, and administrative efficiency. Of these, 9 studies were conducted in the United States, and the remainder spanned global or multi-country settings, including Taiwan, Japan, Bengal articles[12-19].

Medical imaging emerged as the most common application area, with nine studies focusing on AI's role in interpreting radiologic, endoscopic, or pathological images [15,16,20,21]. These studies investigated tasks such as detection[15,16,22], diagnosis[16,22-24], reduction of interpretation time [15,16], and workflow optimization [15,16,23].

Nine studies[12,14,17-20,22,24,25]explicitly addressed the health economic impact of AI, including cost savings[12-14,19,20,24] , budget impact[19,20,24] , and reduction in treatment costs[14]. Administrative efficiency was the focus of three studies [13,26], each addressing the potential of AI to automate and streamline non-clinical tasks such as clinical documentation [13,18], and claims processing [13,19].

Table 1 Summary characteristics of included studies

Study	Type	Country	Data	Intervention of Interest
Abramoff et al[21]	Workforce productivity	Bengal	A clinic with a very large demand , Deep Eye Care Foundation (DECF) in Bangladesh	LumineticsCore (IDx-DR) Diabetic eye exams.
Natesan et al [12]	Health economy	The USA	Duke Cancer Center Duke Health System cost accounting system, Medicare, and Medicaid	ML(XGBoost)-identified high-risk courses (≥10% risk of acute care during RT).
Lavoie et al [13]	Administrative Efficiency	The USA	Analysis of existing US healthcare spending data and administrative costs.	Application of AI tools to automate and streamline non-clinical administrative

				processes.
Sahni et al [19]	Health economy	The USA	Expert inputs, McKinsey internal experiments, and published research. National Health Expenditures data (2019)	(ML) applications in healthcare ,(NLP) is used to extract text from clinician notes for documentation or coding.
Kacew et al[14]	Health economy	The USA	Secondary research (peer-reviewed literature and Medicare data)	AI for Cancer Diagnosis Cost.
Yacoub et al [15]	Workforce productivity	The USA	Medical University of South Carolina	AI-Rad Companion.
Hunter et al[16]	Workforce productivity	The USA	Picture archiving and communication system (PACS) single-view CXRs of adult inpatient.	The diagnostic accuracy and impact on radiologist report turnaround times of an FDA-approved AI tool for pneumothorax (PTx) detection on inpatient chest X-rays (CXR) in our institution's radiology practice at a large academic medical center
Worrall et al[22]	Health economy	The USA	Medicare.	AI supports pharmacist-led medication adherence programs.
McKinsey Company et al 2023[17]	Health economy	Global	Extensive global data and expert insights	Generative AI-Product R&D software engineering, Customer documentation generation, Generate content for commercial representatives, Contract generation.
McKinsey Company et al 2020[18]	Health economy Workforce productivity	Global	Extensive global data and expert insights	This definition is deliberately broad; it includes the application of rules-based systems

	Administrative Efficiency			as well as cutting-edge methodologies that include classic machine learning, representation learning and deep learning. Examples of AI applications would include NLP, image analysis and predictive analytics based on machine learning.
Mori et al [20]	Health economy	Japan	Large-scale single-center clinical trial	EndoBRAIN
Dembrower et al[27]	Workforce productivity	Sweden	Karolinska University Hospital	Ai based triaging of breast cancer screening mammograms.
Rozario et al[26]	Administrative Efficiency	Canada	Oakville Trafalgar Memorial Hospital	Python programming language combined with the open source OR-Tools software suite from Google AI.
Willmen et al[24]	Health economy	Germany	Hannover Medical School.	A Diagnostic Decision Support System (DDSS) is an artificial intelligence–based system that supports physicians in diagnosing rare diseases.
Lauritzen et al[28]	Workforce productivity	Danish	A single European institution.	Transpara employs deep convolutional neural network (DCNN) technology to detect suspicious breast. cancer lesions on full-field digital mammography.
Tong et al[29]	Workforce productivity	China	First Affiliated Hospital of Sun Yat-sen University and the Third Affiliated.	A deep learning AI model assists in improving the diagnostic accuracy of

			Hospital of Sun Yat-sen University.	thyroid nodules by enhancing the performance of ultrasonographic diagnosis.
Brix et al[25]	Health economy	Finland	Hospital's radiology information system (RIS).	Deep Resolve Boost enhances MRI scanner throughput and significantly shortens MRI scan time while maintaining or improving image quality.
Chen et al[30]	Workforce productivity	Taiwan	Chi Mei Medical Center.	A+ Nurse is a ChatGPT-based large language model (LLM) tool that enhances the efficiency and accuracy of nursing documentation.
Ahsen et al[31]	Workforce productivity	Korea	A tertiary hospital in South Korea.	A commercially available DLD. The algorithm was designed to identify suspicious areas for 9 abnormal radiologic findings.
Almagharbeh et al[32]	Workforce productivity	Jordan	Two governmental hospitals and three private hospitals in Amman, Jordan.	AI-based decision support systems (DSS) on the operational processes of nurses in critical care units (CCU).
Evans et al[33]	Administrative Efficiency	Australia	One allied health organization.	Lyrebird Health is an AI medical scribe.
Hadi et al[34]	Workforce productivity	Saudi Arabia	The radiology department of a tertiary referral hospital in Makkah, Saudi Arabia.	ChatGPT-4o.
McKinney et al[35]	Workforce productivity	the UK and the USA	UK National Health Service Breast Screening Programme and Northwestern	AI system that is capable of surpassing human experts in breast cancer prediction.

			Memorial Hospital (Chicago).	
Kyono et al[36]	Workforce productivity	the UK	Six UK National Health Service Breast Screening Program centers.	The Autonomous Radiologist Assistant (AURA), integrating ML, CNN, DNN, and a hybridized approach, is applied to breast cancer screening.

<u>Impact of Health Economy or Systems-Level Spending</u>

The study, conducted by a team of researchers from Harvard, offers one of the most comprehensive assessments of the potential financial impact of AI in healthcare sector[19]. It estimates that over the next five years, AI could generate annual net savings of $200 billion to $360 billion in the U.S. healthcare sector without compromising quality or access, based on 2019 dollars. This represents a 5% to 10% reduction in total U.S. healthcare spending. The estimate is based on data from the National Health Expenditure, specifically total hospital revenues and total hospital costs[19].

Complementing these quantitative projections, the EIT Health & McKinsey report highlights AI's systemic role in sustaining healthcare delivery under financial and workforce pressures, particularly in Europe, by enhancing productivity and enabling more proactive models of care[18]. At a broader economic frontier, McKinsey's assessment of generative AI estimates an annual global value creation of USD 2.6–4.4 trillion, with USD 60–110 billion accruing specifically to the pharmaceutical and medical-product industries, pointing to further downstream effects on healthcare affordability and innovation[17].

<u>Costs Reduction or Saving for Treatment</u>

Few studies identifying cost savings associated with the use of AI. s. One example is provided by Mori et al., who analyzed AI-aided colonoscopy for polyp diagnosis. They compared traditional methods with an AI-aided approach for detecting diminutive colorectal polyps. Their findings indicated reductions in average colonoscopy costs of approximately 18.9% in Japan, 6.9% in England, 7.6% in Norway, and 10.9% in the United States. Thus, the use of AI results in substantial cost savings for colonoscopy[20]. A study on metastatic colorectal cancer demonstrates that deploying high-sensitivity AI for MMR/MSI status determination, followed by confirmatory testing for negative cases, resulted in projected savings of $400 million—approximately 12.9% of total diagnostic and treatment costs—compared to next-generation sequencing alone [14]. Another cost analysis focusing on machine learning-guided radiotherapy interventions showed a statistically significant reduction in acute care visits and a halving of treatment costs per course ($1,494 vs. $3,110), suggesting strong cost-efficiency when targeting high-risk cases using AI triage [12,14].

Additionally, a retrospective study showed substantial cost reductions through improved medication adherence and patient outcomes using AI. Findings indicated that after the introduction of a pharmacist-led, AI-supported program, medication adherence improved across all disease measures. Importantly, adherent patients demonstrated notable reductions in overall healthcare expenditures compared to nonadherent patients, with cost savings of 31% for hypertension, 25% for hyperlipidemia, and 32% for diabetes. However, external validity may be limited by claim data constraints, potentially impacting the reflection of actual clinical outcomes due to missing or inaccurate data[22].

Efficiency Gains in Medical Imaging

In radiology, the implementation of an AI tool for pneumothorax detection was shown to significantly improve report turnaround time, reflecting measurable gains in workflow efficiency16. Similarly, a prospective randomized study found that integrating an automated AI platform into chest CT interpretation reduced reading time by 22.1%, demonstrating AI's potential to enhance radiologist productivity15. Similarly, in breast cancer screening, an international evaluation published in *Nature* demonstrated that an AI system outperformed radiologists in both the US and UK, reducing false positives by up to 5.7% and false negatives by 9.4%, while cutting second-reader workload by 88%[37].

These findings align with *Transforming Healthcare with AI*, which identifies diagnostic speed and accuracy as key areas where AI is already delivering impact. The report emphasizes that imaging-heavy specialties such as radiology, pathology, and ophthalmology are being actively reshaped by AI, describing imaging applications as "low-hanging fruit" due to their readiness to provide immediate, tangible benefits in clinical settings[18].

Efficiency Gains in Medical Documentation

One study identified clinical documentation as a significant component of administrative costs and discussed how tools such as NLP can extract relevant data from clinical notes. This can help ease documentation demands from payers and accelerate claims approvals, emphasizing the link between documentation processes and administrative efficiency[13].

Similarly, Analysis by McKinsey group notes that AI can take on administrative tasks, including the use of NLP to process clinical notes—highlighting its role in automating clinical documentation and improving workflow efficiency in this area[18].

Recent empirical work further illustrates these benefits in practice. Rozario and colleagues demonstrated that applying a machine-learning optimization model to operating room scheduling significantly reduced overtime by 21%, translating to an estimated cost saving of USD 469,000 over three years[26]. In allied health private practice, Evans et al. found that using an AI scribe decreased time spent on clinical notes and letters, reduced after-hours documentation, and improved both productivity and therapeutic alliance between clinicians and patients[33]. Together, these findings highlight AI's dual potential: streamlining administrative processes while simultaneously enhancing the efficiency and quality of clinical workflows.

Efficiency Gains in Claim Management

In terms of administrative efficiency, AI tools have shown some of the clearest and most immediate benefits[13,18,19]. Studies suggest that automating claims processing, prior authorization, quality assurance, and credentialing could eliminate as much as $168 billion in annual U.S. administrative spending[13]. AI applications in this area include centralized digital claims clearinghouses, NLP-based documentation extraction, and fully electronic prior authorization systems[13]. For instance, centralizing claims processing was estimated to save $300 million annually, while electronic authorization pipelines could yield an additional $417 million in savings. The McKinsey and NBER analyses both highlight administrative automation as a primary driver of system-level savings, estimating that 40–50% of AI-derived cost reductions for hospitals and physician groups stem from back-office and billing functions.

Potential in Claims Management and Member Services: AI could lead to significant savings by addressing repetitive administrative processes such as processing prior authorisations or adjudicating claims. AI-enabled identification models can streamline operations and inform efforts to reduce fraud, waste, and abuse[19] .

Both McKinsey's *Reports* (2020, 2023) highlight AI's transformative potential but differ in scope: the former focuses on AI's role in improving healthcare delivery and reducing system waste, while the latter explores cross-industry automation of knowledge work. Both reports also address labor implications—*The Economic Potential of Generative AI* (2020) points to potential displacement of high-skill tasks, whereas *Transforming Healthcare with AI* emphasizes relieving administrative burdens in healthcare and the importance of digital upskilling. While *Generative AI* focuses on theoretical value creation, *Transforming Healthcare with AI* ties economic gains to specific healthcare efficiencies and underscores the need for governance, funding, and workforce readiness to realize AI's full potential[18,38].

In summary, Figure 2 illustrates a mechanism-based framework that was consistently described across several studies included in this review. Beginning with inputs in the form of AI technologies—including applications in natural language processing, image analysis, and machine learning—the framework highlights the key mechanisms through which these technologies enact change. These include process automation, decision support, and resource optimization. As these mechanisms are embedded into healthcare operations, they contribute to measurable improvements in productivity, efficiency, and service quality. These system-level outcomes, in turn, drive economic impact through cost savings, improved health outcomes, and better use of resources. This pathway emphasizes that the economic benefits of AI are not simply a function of the technology itself, but rather emerge from its integration into and influence on health system processes.

Figure 2- Mechanism of AI application impact health economy

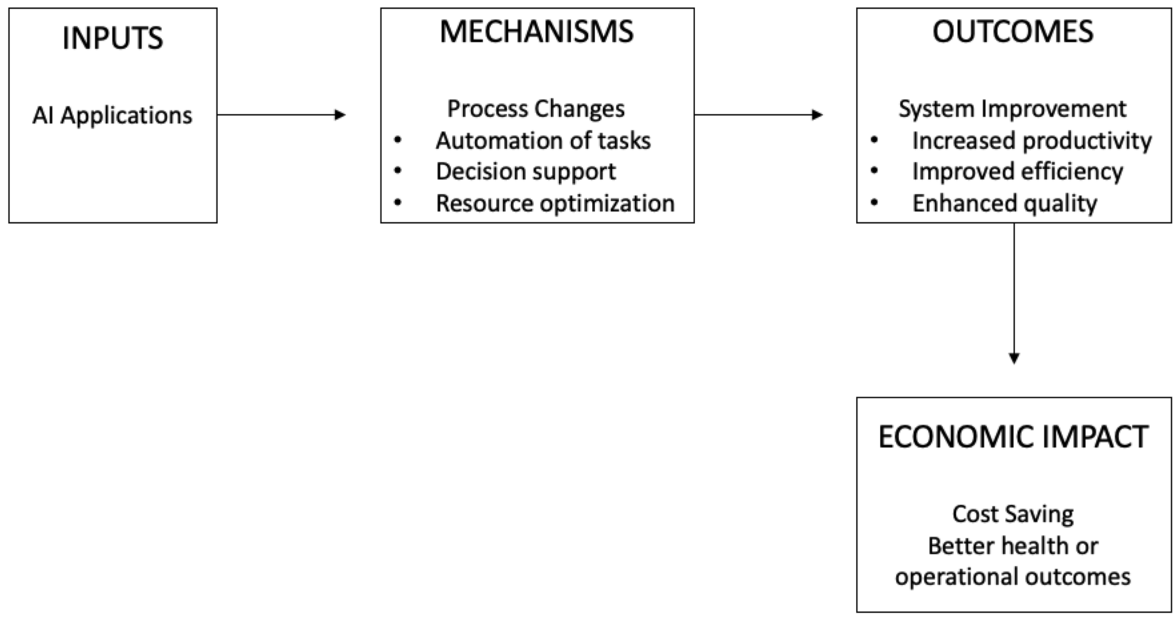

INPUTS
AI Applications
MECHANISMS
Process Changes
Automation of tasks
Decision support
Resource optimization
OUTCOMES
System Improvement
Increased productivity
Improved efficiency
Enhanced quality
ECONOMIC IMPACT
Cost Saving
Better health or operational outcomes

Table 2. Methodological Approaches for Examining Health Economy Outcomes

Study	Measurement	Statistical Method	Findings	Limitations
Natesan et al [12]	The primary outcome was difference in mean total medical costs during and 15 days after RT.	A cost-minimization analysis was conducted to compare the standard treatment strategy with the intervention approach. randomized controlled study.	Significant reduction in total healthcare costs: After adjusting for patient and disease factors, the average total healthcare cost per treatment course was significantly lower in the intervention group at $1,494, compared to $3,110 in the standard care group (P = 0.03).	Nonfinancial benefits, such as improvements in patient health, were not considered. A 10% risk threshold for intervention was selected based on available personnel resources.
Kacew et al[14]	Total costs of testing and first-line therapy across different diagnostic strategies for determining MMR/MSI status in metastatic colorectal cancer.	Financial and clinical modelling to compare costs of different diagnostic algorithms (NGS alone, PCR/IHC panel alone, AI-based strategies with and without confirmatory tests).	The testing strategy that resulted in the greatest project cost savings (including testing and first-line drug cost) compared to next-generation sequencing alone in newly-diagnosed metastatic colorectal cancer was using high-sensitivity artificial intelligence followed by confirmatory high-specificity polymerase chain reaction or immunohistochemistry panel for patients testing negative by artificial intelligence ($400 million, 12.9%).	The recent study used theoretical models, and its results need to be validated using real-world data. • The accuracy of the estimates depends on the validity of the various sources used to establish the model input assumptions.
Sahni et al[19]	Potential net savings opportunity across	Estimate a gross savings percentage for each	AI adoption within the next five years could result in savings of 5 to 10 percent of health	The insights are not based on randomized control trials or quasi-experimental evidence.

	different healthcare stakeholders by using existing AI technologies	domain. Breaking down the industry into five stakeholder groups.	care spending, or $200 billion to $360 billion annually in 2019 dollars	Focus only on what is possible using existing technologies.
Worrall et al[22]	Medication Adherence Measures Disease Control Measures Overall health care expenditures (cost saving)	Retrospective, quasi-experimental analysis.	A reduction of $3388 per member per year and $282 per member per month in total cost of care.	Claims Data may be inaccurate, limited ability to reflect actual clinical outcomes, limited representativeness. Only an approximation of actual medication-taking behavior.
McKinsey Company et al 2023[17]	Economic Potential R&D Efficiency	To assess the potential value of generative AI, they updated a proprietary McKinsey database of potential AI use cases and drew on the experience of more than 100 experts in industries and their business functions.	Generative AI could have a significant impact on the pharmaceutical and medical-product industries—from $60 billion to $110 billion annually. Improve automation of preliminary screening.	The need for a human in the loop Explainability Privacy considerations
Mori[20]	cost per colonoscopy and gross annual reimbursement for colonoscopies	Average costs per colonoscopy based on the worst-case scenario.	In Japan the average colonoscopy cost under the diagnose-and-leave strategy (supported by AI prediction) was US$119 lower, The expected gross annual reimbursement savings for	Single-center study Potential overestimation of AI performance

			colonoscopies would be US$149,220,133.	
McKinsey Company et al 2020[18]	A comprehensive understanding of AI's impact in healthcare, encompassing multiple dimensions including technology, economics, workforce, regulation, and user experience.	Qualitative and Quantitative Analysis.	AI has tremendous potential to transform healthcare by improving care outcomes, patient experience, and access to medical services, while also enhancing efficiency.	N/A
Willmen et al[24]	Costs	Descriptive statistics.	DDSS can achieve up to a 50% cost reduction by avoiding unnecessary duplicate tests and by enabling faster diagnosis.	The study employed a retrospective approach, and the results are exploratory in nature. Case scope limitation: The patient cases examined represent only a small subset of specific rare diseases; therefore, the findings cannot be generalized to all rare diseases.
Brix et al[25]	Annual total cost savings.	Comparative analysis of financial feasibility.	This investment is expected to save €399,000 annually in MRI service costs.	The revenue changes resulting from the increase in MRI examinations cannot be directly generalized to other regions.

Table 3. Methodological Approaches for Examining Administrative Efficiency

Study	Measurement	Statistical Method	Findings	Limitations
Lavoie et al [13]	Potential for cost savings by	Not clear.	Adoption of these tools can eliminate $168	Assessing administrative

	leveraging AI to streamline billing, insurance, credentialing, and quality assurance processes.		billion in annual administrative costs.	costs is difficult given the limited transparency and lack of standardized reporting practices.
Rozario et al[26]	Overtime frequency, Undertime frequency, Overtime minutes and used Overtime cost.	Assessed retroactively.	Overtime reduced by 20.99%, Undertime reduced by 19.03% and On-time increased to 55%.	Requires programming skills to implement.
Evans et al[33]	Productivity and percentage of time AHPs reported using the AI scribe.	Inferential Statistics.	saving approximately 17-min per day on clinical notes and 9-min per day on letters. Productivity increased by an average of 5.8 %.	All allied health professional (AHP) participants were recruited from a single organization, which may limit the generalizability of the findings. Potential sampling bias.

Table 4. Methodological Approaches for Examining Workforce Productivity

Study	Measurement	Statistical Method	Findings	Limitations
Abramoff et al [21]	Clinic productivity (number of completed care encounters per hour per specialist physician)	$\lambda = n_q$ / t n_q is the number of patients who completed a care encounter with a quality of care that was non-inferior to q, and t is the length of time over which was measured.	AI leads to 40% higher productivity Secondary endpoint (productivity in all patients) was also met. .	The study was conducted within a single health system in a low-income country, involving only three physician specialists and focusing on a single disease. As such, the findings may not be generalized to other settings, medical conditions, or AI systems.

Yacoub et al [15]	Reduce physicians' CT interpretation time.	The interpretation time is defined as the duration from when the case is first opened in the PACS to when the final report is signed.	For readers combined, the mean difference was 93 seconds (95% CI, 63–123 seconds), corresponding with a 22.1% reduction in the AI-assisted arm.	The AI-assisted and non–AI-assisted scans were from different patient cohorts, introducing potential confounders. Radiologists' awareness of the study could have biased interpretation time. Conducted at a single center using one AI platform, the findings may not be generalizable. The study did not assess AI's impact on diagnostic accuracy, and classification of findings was subjective. It also remains unclear how radiologists used the AI output or why it reduced interpretation time, .
Hunter et al [16]	Comparison of reporting times	Measured reporting time by calculating the time interval between when the image appeared in the PACS and when the radiologist—radiology resident during on-call hours—completed the preliminary report. For daytime cases without resident involvement, the time of the final report was used	Median reporting time in CXRs with radiologist-confirmed PTx was reduced by 46% in those with AI integration as compared to those without AI integration	The main limitations of the study lie in its retrospective nature and the imbalance in baseline characteristics between the AI and control groups, particularly in the incidence of pneumothorax and the proportion of STAT priority studies.

		instead.		
Dembrower et al[27]	Proportion of screen-detected cancers that would have been missed	Retrospective simulation study.	Using a commercial AI cancer detector to triage mammograms into no radiologist assessment and enhanced assessment, could potentially reduce radiologist workload by more than half.	did not study the full screening cohort, but instead used a case-controlled design.
Lauritzen et al[28]	Workload reduction: calculated as the percentage of mammograms interpreted solely by the AI system.	Direct calculation.	The radiologists' workload was reduced by 62.6%.	Under the AI screening protocol, the subset of mammograms reviewed by radiologists may have a higher likelihood of cancer compared to standard screening.
Tong et al[29]	Reduced diagnostic time.	Paired-sample t tests.	For one junior radiologist, it increased by approximately 4.3 seconds, while for one senior radiologist, it decreased by approximately 2.6 seconds.	The study did not examine the interpretability of the deep learning algorithm.
Chen et al[30]	Documentation time.	Direct time comparison.	Cutting down documentation time from 15 to about 5 minutes per patient without sacrificing quality.	N/A
Ahsen et al[31]	Sensitivity	One-sided noninferiority test.	Reduce workload by 50% while maintaining diagnostic accuracy	A single-center study with a retrospective design. Arbitrarily set a thresh-old for worklist reduction at 50% for

				primary analysis.
Almaghar beh et al[32]	Nursing workflows, including time management, efficiency, decision-making, and AI-based DSS impact.	Not clear.	With 42.9% nurses noting significantly improved efficiency and accuracy, whereas28.6%nurses reported somewhat improved efficiency and accuracy.	The study employed a cross-sectional analysis, which cannot establish causal relationships.
Hadi et al[34]	Acquisition time (in minutes).	Quantitative analysis.	Acquisition time' for scans also decreased from 15.4 minutes to 11.1 minutes.	A relatively short data collection period and purposive sampling
McKinney et al[35]	Reduction of the second reader's workload percentage.	Simulation.	Reduced the workload of the second reader by 88%.	These simulation-based results require prospective clinical trials to validate their benefits and confirm the impact on real-world patient care workflows.
Kyono et al[36]	The proportionate reduction in the number of mammograms a radiologist needs to read.	Logistic regression analysis.	In the test set with a cancer prevalence of 15%, AURA identified 34%; in the test set with a cancer prevalence of 1%, AURA excluded nearly 91%, eliminating the need for radiologist review.	The actual workload impact has not yet been empirically tested.

Analytical Approaches and Statistical Methods

The studies included in this review employed a diverse range of analytical approaches to estimate the impact of AI on healthcare costs, productivity, and efficiency. At the broader economic level, macroeconomic modeling and bottom-up use-case analysis were used to forecast potential system-level savings. For instance, Sahni et al.[19] estimate that wider adoption of AI could lead to savings of 5% to 10% in U.S. healthcare spending—approximately $200 to $360 billion annually in 2019 dollars. These estimates are based on specific AI-enabled use cases that utilize current technologies and are attainable within the next five years without compromising quality or access. Their approach involved mapping specific healthcare tasks (e.g., administrative work, diagnostics, operations support) to AI capabilities and estimating time and cost reductions from AI adoption across sectors like payer services and hospital operations. This analysis offers a macroeconomic view of how AI could reshape healthcare spending patterns if deployed at scale.

In contrast, scenario-based cost modeling has also been applied to specific clinical workflows. Kacew et al.[14] evaluated eight diagnostic strategies for determining mismatch repair/microsatellite instability (MMR/MSI) status in metastatic colorectal cancer. Their analysis found that a strategy combining high-sensitivity AI with confirmatory high-specificity PCR or IHC testing resulted in the greatest cost savings—approximately $400 million (12.9%)—compared to next-generation sequencing alone. Additionally, a high-specificity AI-only approach provided the shortest time to treatment initiation (<1 day) and maintained a 97% rate of patients receiving guideline-supported therapy.

Experimental and quasi-experimental designs were also employed to directly quantify changes in healthcare productivity resulting from AI use. A notable example is the cluster-randomized trial by Abramoff et al.[21], which examined the use of an autonomous AI system for diabetic eye exams in primary care. The study used queueing theory to model clinic workflows and measured productivity by the number of completed patient encounters per hour. Clinics using the AI system achieved a 40% increase in throughput compared to controls, highlighting the operational gains achievable through autonomous decision-making tools.

DISCUSSION

This review synthesizes current evidence on the macro-level effects of artificial intelligence (AI) across three critical domains of health system performance: the health economy, workforce productivity, and administrative efficiency. Across these domains, AI—particularly in the form of machine learning algorithms, generative models, and natural language processing systems—demonstrates substantial promise in generating cost savings, enhancing operational throughput, and improving workflow efficiency.

In the economic domain, analyses from sources such as McKinsey and the National Bureau of Economic Research estimate that scaled AI implementation could reduce national health expenditures by 5 to 10 percent. These projected savings are primarily attributed to automation of clinical and administrative processes and the deployment of predictive analytics. However, these forecasts are based on optimistic assumptions, and their applicability across healthcare systems with varying regulatory and infrastructural contexts remains uncertain.

AI has also shown promise in mitigating workforce inefficiencies. Applications such as ambient AI and large language models are increasingly used to automate clinical documentation and accelerate diagnostic workflows. Systematic reviews have reported significant reductions in diagnostic time—occasionally exceeding 90 percent. However, such gains are offset by ongoing concerns about the accuracy, reliability, and contextual coherence of AI-generated content, particularly in documentation where clinical nuance and narrative detail remain essential.

Administrative functions—including claims processing, prior authorization, and provider credentialing—emerge as particularly well-suited to AI-enabled automation. These high-cost, low-clinical-risk tasks present opportunities for efficiency, standardization, and transparency, with relatively lower ethical and safety concerns. As such, they may serve as practical entry points for broader AI integration at the system level.

Limitations of Existing Studies

While the research on AI in healthcare is growing fast, there are still some major gaps we need to talk about. First, a lot of the studies are short-term, so we don't really know how AI tools perform over the long run or how they change actual patient outcomes. Also, many of them rely on very specific patient groups or are based in just one or two hospitals, which means the findings might not apply to everyone. Another big issue is that most studies don't break down their results by race, income level, or social background, so we're missing a clear picture of whether AI is helping or hurting when it comes to health equity. On top of that, some studies struggle with confounding factors—like whether certain types of patients are more likely to get AI-assisted care—which can muddy the results. And finally, while we know that introducing AI can shake up how people work, very few papers look into the real-world barriers to getting these tools adopted, such as whether clinicians trust the tech or how it fits into their daily routines. So even though the potential is huge, there's still a lot we don't fully understand.

Despite the potential of artificial intelligence to enhance efficiency and reduce costs in healthcare, its unintended consequences warrant careful consideration. Overreliance on AI may erode clinicians' diagnostic judgment, leading to skill degradation, increased risk of misdiagnosis, and the resulting costs of medical errors and retraining[39,40]. If training data used for AI models is biased, the technology may deliver inequitable outcomes, disproportionately impacting minority groups and further exacerbating health disparities, with increased long-term costs due to preventable disease progression[41,42]. While AI can improve diagnostic sensitivity, it may also result in incidental findings and overtreatment, contributing to the waste of limited healthcare resources. Furthermore, the vast amount of health data required by AI systems poses significant privacy and cybersecurity risks; data breaches may lead to legal liabilities and high infrastructure costs, especially burdensome for smaller institutions[43,44]. Although AI can alleviate workforce burdens, it may disrupt labor markets by displacing certain roles and creating reskilling needs. Highly specialized algorithms may also fragment care delivery, reducing coordination and integration. To mitigate these risks, the implementation of AI must be grounded in careful governance and equitable model design to ensure that it strengthens—rather than undermines—high-quality, patient-centered care[45,46].

Research and Policy Implications

Artificial intelligence is speeding image reading, documentation, and administrative workflows, but supporting evidence remains scattered across small pilots, heterogeneous designs, and simulations, hindering comparison and generalization[47 48]. Future studies should adopt shared efficiency metrics—time saved per case, full cost-utility ratios that include upkeep, and indicators such as user trust and alert overrides—while embedding prospective mixed-methods evaluations in routine care to link data quality, culture, and interface design with short-term performance and long-term sustainability[49]. Economic work must count real deployment costs—retraining, integration, workforce preparation—so decision-makers see net value, not idealized savings[47,50].

It's worth to note that efficiency gains alone will not necessarily ease shortages: while in nursing, AI may enhance nurses' work-life balance[51], some physicians are worried that they may have to see more patients in the case[52]. Large-scale deployments therefore need labor-market impact assessments that shape staffing benchmarks, reskilling programs, and wage structures, keeping progress humane[38]. Because data distributions shift—dramatically so during events like COVID-19—models need continual calibration and monitoring[53]; governance should mandate drift-detection dashboards, external validation, and agile updates[48].

On top of that, early studies already flag automation bias. Prinster et al[54]. showed feature-based explanations improve accuracy yet foster faster, less critical acceptance, while Patil et al[55]. warn that unquestioned trust may heighten burnout and liability. Both were short term; longitudinal work must test whether routine exposure blunts clinicians 'ability to spot hallucinations or edge-case errors.

Before nationwide deployment, small and representative pilots should precede national roll-outs, revealing how diverse users weigh AI advice and guiding interface refinements. Budgets must fund these cycles of testing, training, recalibration, and monitoring[50], acknowledging hidden implementation costs and AI's lifelong upkeep. To close evidence gaps, stepped-wedge cluster trials[56], difference-in-differences analyses[57], and sequential mixed-methods studies—supplemented by long-term drift-monitoring cohorts—may yield causal, scalable insights while capturing behavioral adaptations and safety signals. Paired with transparent cost accounting and workforce modules, such designs will turn scattered demonstrations into a robust evidence base.

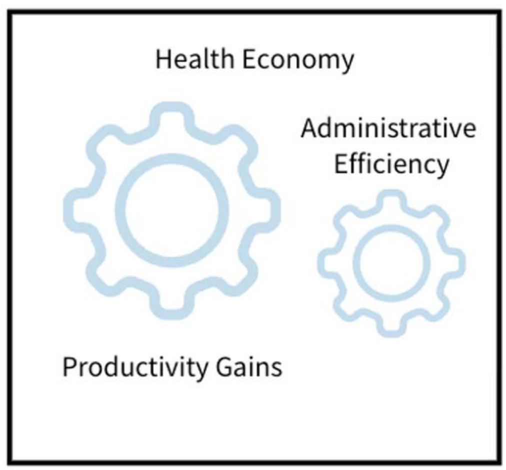
Current evidence on economics of AI is constrained by methodological heterogeneity, limited use of real-world implementation data, and a predominant reliance on theoretical and algorithmic models. While projections suggest substantial savings and operational gains, these benefits remain contingent on how AI is integrated within complex clinical environments that allow widespread adoption of the technology. Policy strategies that align regulatory safeguards with practical implementation challenges—while addressing trust, data governance, and equity—will be central to realizing the sustainable value of AI in healthcare.

METHODS

This study employed a systematic review methodology to synthesize existing literature on the macro-level impact of AI on healthcare systems, with a specific focus on health system costs and spending, workforce productivity, and administrative efficiency. Unlike systematic reviews, the systematic review approach allows for the integration of diverse types of evidence, making it particularly well-suited to emerging and multidisciplinary topics such as AI-driven health system reform.

Figure 1 illustrates the conceptual framework guiding this review. The framework positions AI as a system-level catalyst capable of generating gains across three interrelated domains: health economy, workforce productivity, and administrative efficiency. The overlapping nature of these gears reflects the interconnected effects of AI interventions, in which improvements in one area (e.g., administrative automation) may drive ripple effects in overall cost savings and labor optimization.

Figure 1- Conceptual framework of the impact of AI on health economy

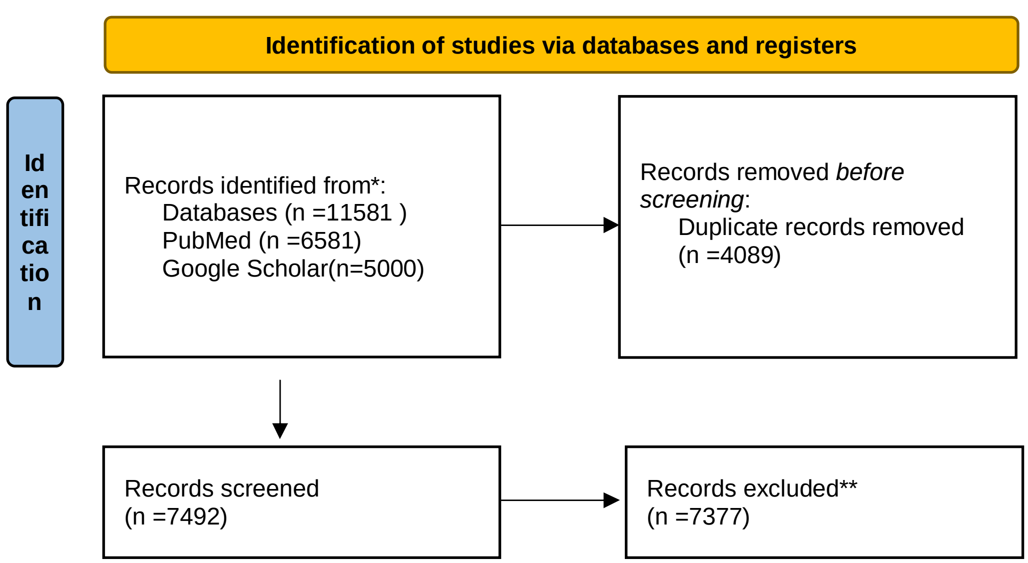


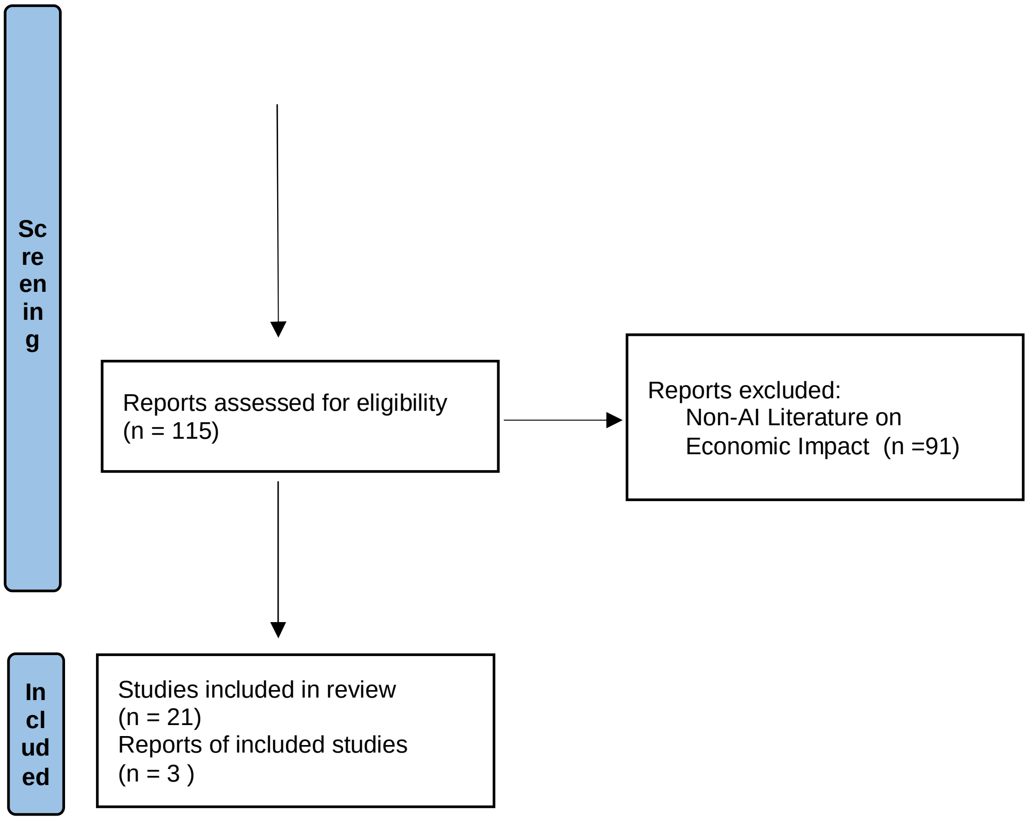
A comprehensive literature search was conducted using four major databases: PubMed, and Google Scholar. The search covered literature published between January 2020 and July 28 2025. Keywords and Medical Subject Headings (MeSH) were selected to reflect the core themes of the study, including terms related to artificial intelligence (such as “AI,” “machine learning,” “natural language processing,” “Neural Networks,” “Computer-Assisted Diagnosis,” “Decision Support Systems, Clinical,” “digital health,” “artificial intelligence-assisted,” “artificial intelligence-based,” “artificial intelligence-aided,” “deep learning,” “neural networks,” “AI intervention s,” “clinical decision support,” “computer aided,” and “predictive analytics”), health system economics (including “health expenditure,” “healthcare cost,” “Cost-Benefit Analysis,” “Cost Savings,” “cost analysis,” “economic impact,” and “health care cost reductions”), workforce and productivity (such as “workforce,” “workload,” “productivity,” “workload reduction,” “labor productivity,” “health systems,” “health systems,” interpretation times and “"clinician workload”), and administrative efficiency (including “Efficiency, Organizational," "administrative efficiency," "Workflow," "documentation time," "claims processing," "reporting times," "administrative burden," and "workflow efficiency"). Boolean operators were used to structure the search and connect concept clusters, allowing for the inclusion of studies that explored intersections such as AI and health spending or AI and administrative efficiency.

Studies were eligible for inclusion if they examined the macro-level impact of AI on healthcare systems and reported outcomes related to total cost, national or regional health expenditure, workforce productivity, or the efficiency of administrative processes. Eligible studies employed empirical methods, simulation models, structured reviews, or policy analysis and were published in peer-reviewed journals or as policy reports from reputable health or economic institutions. Studies were excluded if they focused solely on patient- or clinic-level cost-effectiveness or cost-utility analyses; if they discussed only clinical outcomes without broader system-level implications; if they presented algorithm development without application to system performance; if they lacked clear data or methodological frameworks; or if they were non–peer-reviewed publications such as commentaries, editorials, or opinion pieces.

Given the systematic structure of this review, the synthesis of findings was conducted thematically, guided by the three pre-specified domains: health system costs and macro-level spending, workforce productivity and labor restructuring, and administrative efficiency and system process optimization. The analysis also aimed to identify recurring themes, gaps in the evidence, methodological challenges, and insights specific to regional or health system contexts. For each included study, relevant information was extracted, including the country or region of study, the domain of AI application, study design, outcome measures, and key findings related to cost, productivity, or administrative efficiency. A flow diagram of records found, screened, selected, and excluded with corresponding exclusion criteria is shown in Figure 2. The remaining 24 studies were read full text.

Figure2-PRISMA flowchart describing study selection and reasons for exclusion during full-text screening.





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Author contributions
J.T.L. conceived the study. J.T.L, V.T.L and wrote the first draft of the manuscript. V.T.N.L., V.C.S.L., C.W.H. and H.H.C. reviewed the article. All authors contributed to writing the second draft and have read and approved the final manuscript.

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