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Original Article

The Economic Impact of AI Adoption in Healthcare: Estimating National Cost Savings, Productivity Gains, and Long-Term Health Outcomes

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Abstract - *Artificial intelligence (AI) is increasingly being adopted across healthcare systems to improve diagnostic accuracy, streamline administrative processes, strengthen clinical decision-making, and support preventive care. However, its national economic implications remain insufficiently understood, particularly regarding healthcare cost savings, workforce productivity, and long-term population-health outcomes. This study develops an evidence-informed national economic modelling framework to estimate the potential impact of AI adoption across key healthcare functions, including diagnostic imaging, automated screening, clinical decision support, predictive risk management, telehealth, and administrative automation. The framework compares current healthcare delivery with low-, moderate-, and high-adoption AI scenarios over a ten-year period. Economic outcomes include direct medical cost savings, reduced avoidable hospitalizations, improved diagnostic efficiency, clinician and administrative time savings, increased service capacity, and long-term health benefits measured through avoided complications and quality-adjusted life years. The analysis also incorporates implementation, maintenance, workforce-training, data-infrastructure, and governance costs to estimate net economic value. The study argues that AI can generate substantial national value when deployed in high-volume, high-cost, and prevention-oriented services. Nevertheless, financial benefits depend on interoperable health-data systems, clinical integration, algorithmic accuracy, human oversight, equity safeguards, and continuous performance monitoring. The proposed framework offers policymakers a practical basis for prioritizing responsible AI investments that improve both healthcare efficiency and long-term patient outcomes.*

Keywords *- Artificial Intelligence, Healthcare Economics, Cost-Effectiveness, National Health Expenditure, Workforce Productivity, Health Outcomes, Digital Health.*

1. Introduction

1.1. Background and Context

Healthcare systems across the world are under increasing financial and operational pressure. Population ageing, the growing prevalence of chronic diseases, workforce shortages, rising treatment costs, and inefficient administrative processes have made it increasingly difficult for health systems to deliver timely, high-quality, and financially sustainable care. Chronic conditions such as diabetes, cardiovascular disease, cancer, and respiratory illnesses require long-term monitoring, repeated treatment, and coordinated care, thereby increasing demand for healthcare resources. At the same time, hospitals and primary-care facilities must manage rising patient volumes while addressing shortages of clinicians, nurses, technicians, and administrative personnel.

Artificial intelligence (AI) has emerged as a potentially important tool for responding to these pressures. In healthcare, AI includes machine-learning algorithms, predictive analytics, natural-language processing, computer vision, clinical decision-support systems, and automated workflow technologies. These tools can analyse large volumes of clinical, administrative, imaging, laboratory, and population-health data more quickly than traditional manual processes. AI can support earlier diagnosis, disease-risk prediction, treatment planning, patient monitoring, workflow optimisation, and population-health management (Hamet & Tremblay, 2017; Jiang et al., 2017; Rajkomar et al., 2019; Secinaro et al., 2021).

AI is particularly relevant in healthcare because many clinical decisions depend on complex and rapidly expanding information. For example, AI-enabled systems can assist clinicians in interpreting medical images, identifying patients at risk of deterioration, predicting hospital readmissions, prioritising high-risk cases, and supporting screening programmes. Such capabilities may help health systems improve the speed and consistency of care while reducing delays associated with manual data review and fragmented information systems. AI can also support administrative functions through automated documentation, coding, appointment scheduling, claims processing, and management of electronic health records.

Importantly, AI should be viewed as a tool that supports healthcare professionals rather than replaces them. Clinical

judgement, patient communication, ethical decision-making, and accountability remain essential components of healthcare delivery. AI systems can assist clinicians by identifying relevant patterns in large datasets, highlighting potential risks, and reducing repetitive tasks that consume time and attention. This may allow healthcare workers to focus more on direct patient care, complex decision-making, and communication with patients and families (Topol, 2019; Davenport & Kalakota, 2019; Shortliffe & Sepúlveda, 2018).

However, the value of AI cannot be determined only by technical accuracy or algorithmic performance. A highly accurate AI system may still provide limited value if it is expensive to implement, difficult to integrate into clinical workflows, poorly accepted by staff, or inaccessible to underserved populations. Therefore, AI adoption should be evaluated according to its impact on clinical outcomes, health-system expenditure, workforce capacity, service efficiency, patient access, and equity. Successful implementation requires reliable data, effective governance, clinical validation, interoperability, staff training, and continuous monitoring of potential risks and unintended consequences (Kelly et al., 2019; Panch et al., 2018).

1.2. Problem Statement

Although AI is increasingly promoted as a solution to healthcare inefficiency, the evidence regarding its broader national economic impact remains fragmented. Existing studies often examine individual technologies, specific diseases, or pilot programmes rather than estimating the combined effect of AI adoption across an entire healthcare system. For instance, economic evaluations may focus on AI-assisted diagnostic imaging, diabetic-retinopathy screening, cancer detection, or risk prediction in a particular care setting. While these studies provide valuable evidence, they do not fully explain how AI may influence national healthcare expenditure, workforce productivity, service capacity, and long-term population-health outcomes.

Previous reviews have identified substantial variation in the methods, assumptions, and reporting standards used in economic evaluations of healthcare AI. This makes it difficult for policymakers to compare interventions, estimate long-term value, or determine which AI investments should be prioritised. Wolff et al. (2020) observed that economic evidence on AI in healthcare remains limited and heterogeneous, while von Wedel and Hagist (2020) highlighted the growing but uneven evidence concerning the economic value of health data and analytics. Similarly, Al Meslamani (2023) argued that the long-term economic implications of AI adoption require greater attention beyond initial implementation and short-term efficiency claims.

National healthcare systems therefore need a transparent and evidence-informed framework for determining whether AI investments provide value for money. Such a framework should assess not only direct cost savings but also productivity gains, avoided hospital utilisation, improved diagnostic efficiency, enhanced prevention, and long-term health outcomes. It should also account for implementation costs, data infrastructure requirements, governance safeguards, workforce readiness, and equity considerations.

1.3. Aim, Objectives, and Research Questions

The aim of this study is to develop a national-level economic framework for estimating the cost savings, productivity gains, and long-term health outcomes associated with AI adoption in healthcare. The study has five objectives. First, it identifies the major pathways through which AI may reduce healthcare expenditure, including reduced administrative costs, improved diagnostic efficiency, and lower avoidable hospital utilisation. Second, it estimates potential productivity gains for clinicians, administrators, and healthcare facilities. Third, it examines how AI-enabled prevention, screening, and clinical decision support may influence long-term health outcomes. Fourth, it compares low-, moderate-, and high-adoption scenarios to assess how the scale of implementation influences economic value. Finally, it identifies the governance, equity, and implementation conditions necessary for AI to generate sustainable national healthcare benefits.

Accordingly, the study addresses four research questions:

1. Which healthcare functions offer the greatest potential for AI-related cost savings?
2. How can AI adoption affect workforce productivity and service capacity?
3. What long-term health gains may arise from earlier detection, improved risk prediction, and better treatment decisions?
4. Under what conditions does AI adoption become cost-effective at national scale?

2. Literature Review and Economic Evidence Base

2.1. AI Applications with Economic Relevance

Artificial intelligence (AI) has significant economic relevance in healthcare because it can improve how services are delivered, prioritised, and managed. Major applications include automated medical imaging, diabetic-retinopathy screening, cardiovascular-risk prediction, intensive-care management, breast-cancer screening, lung-cancer screening, and clinical decision support. Across these areas, AI may reduce diagnostic delays, improve referral accuracy, identify high-risk patients earlier, and prevent avoidable complications. Its economic value is therefore linked to reduced resource use, more efficient allocation of specialist time, improved service capacity, and better long-term patient outcomes.

Diabetic-retinopathy screening provides a strong example of this potential. Autonomous AI systems can analyse retinal images in primary-care or community settings, allowing patients to be screened without immediate specialist interpretation. Abràmoff et al. (2018) demonstrated the clinical utility of an autonomous AI diagnostic system for diabetic-retinopathy detection in primary-care offices. At a wider health-system level, this approach may expand screening coverage, reduce referral delays, and direct ophthalmology services toward patients requiring specialist

treatment. Xie et al. (2020) similarly showed that AI-supported teleophthalmology could strengthen national diabetic-retinopathy screening programmes by increasing efficiency and improving referral pathways. Wolf et al. (2020) further indicated that autonomous point-of-care diabetic-retinopathy screening may be cost-effective for paediatric patients with diabetes.

AI also has economic relevance in cardiovascular and critical-care settings. AI-supported cardiovascular imaging can improve image interpretation, standardisation, and early detection of clinically important abnormalities, potentially reducing repeated examinations and delays in treatment decisions (Dey et al., 2019). Machine-learning risk prediction can help identify patients most likely to benefit from atrial-fibrillation screening, allowing healthcare resources to be targeted more efficiently (Hill et al., 2020). In intensive-care settings, predictive AI tools may identify patients at risk of untimely discharge, reducing avoidable readmissions, complications, and extended treatment costs (de Vos et al., 2022). Similar benefits may arise in breast- and lung-cancer screening, where earlier detection can reduce the clinical and financial burden associated with late-stage disease.

2.2. Cost-Effectiveness and Budget-Impact Evidence

Economic evaluation assesses whether an intervention provides sufficient health benefit relative to the resources required for its implementation. Core principles include incremental costs, incremental outcomes, quality-adjusted life years (QALYs), incremental cost-effectiveness ratios (ICERs), discounting, and budget-impact analysis. Incremental analysis compares an AI-enabled pathway with usual care, while the ICER estimates the additional cost required to achieve an additional health outcome. Discounting is necessary when costs and health benefits occur over several years. Budget-impact analysis complements cost-effectiveness analysis by examining whether a healthcare system can afford the intervention during a defined implementation period (Gold, 1996; Drummond et al., 2015; Neumann et al., 2016).

Current evidence suggests that AI can be economically favourable in specific clinical settings, although results remain dependent on local costs, disease prevalence, AI performance, and implementation design. Wolff et al. (2020) found that economic evidence for AI in healthcare was limited and heterogeneous, with considerable variation in methods and reported outcomes. Vithlani et al. (2023) similarly identified weaknesses in the conduct and reporting of AI economic evaluations, particularly regarding implementation costs, analytical assumptions, and model transparency. More recently, El Arab and Al Moosa (2025) reported growing evidence of favourable cost-effectiveness and budget impact, while emphasising that findings cannot automatically be transferred between health systems.

Condition-specific studies illustrate the potential value of AI. Gomez Rossi et al. (2022) found that AI decision support for melanoma, dental caries, and diabetic retinopathy may be cost-effective when it improves diagnostic decisions and reduces unnecessary downstream treatment. In breast-cancer screening, AI-guided risk stratification may improve the targeting of screening resources, although its value depends on screening policies and population characteristics (Mital & Nguyen, 2022; Vargas-Palacios et al., 2023). Ziegelmayer et al. (2022) identified potential cost-effectiveness for AI-supported CT-based lung-cancer screening. Wu et al. (2024) noted that AI-based eye-disease screening is increasingly promising, although results remain sensitive to implementation assumptions. Likewise, de Vos et al. (2022) showed that AI prediction tools in intensive care can create value when risk predictions lead to timely and effective clinical intervention.

2.3. Research Gap

Existing studies provide useful evidence on individual AI applications, but they rarely combine clinical, administrative, workforce, and population-health effects within one national economic framework. Most studies focus on a single disease, technology, or care setting and therefore do not capture the broader interaction between implementation costs, workforce productivity, reduced healthcare utilisation, and long-term health gains. This study addresses this gap by linking micro-level clinical evidence with macro-level estimates of national cost savings, productivity gains, and long-term health-system outcomes.

Table 1: Summary of AI-Enabled Healthcare Applications and Their Expected Economic Pathways

AI application	Clinical setting	Primary economic mechanism	Expected cost-saving pathway	Productivity effect	Long-term health outcome	Key supporting studies
Autonomous diabetic-retinopathy screening	Primary care and teleophthalmology	Automated retinal-image grading	Fewer unnecessary referrals and earlier diagnosis	Releases specialist capacity	Reduced vision loss and complications	Abràmoff et al. (2018); Xie et al. (2020); Wolf et al. (2020)
AI cardiovascular imaging and risk prediction	Cardiology and population screening	Risk stratification and improved image interpretation	Better targeting of tests and earlier treatment	Faster prioritisation of high-risk patients	Reduced cardiovascular events	Dey et al. (2019); Hill et al. (2020)

AI-supported cancer screening	Breast- and lung-cancer programmes	Earlier detection and triage	Reduced late-stage treatment costs	More efficient screening and referral pathways	Improved survival and earlier diagnosis	Mital and Nguyen (2022); Vargas-Palacios et al. (2023); Ziegelmayer et al. (2022)
ICU deterioration prediction	Critical care	Early risk identification	Avoided readmissions and prolonged care	Supports proactive clinical review	Reduced complications and mortality risk	de Vos et al. (2022)

3. Conceptual Framework: National Economic Pathways of AI Adoption

3.1. Economic Pathways

Artificial intelligence (AI) can create national economic value in healthcare through connected clinical, operational, and population-health pathways. Its value does not arise from technology alone, but from improved decisions, reduced inefficiencies, better allocation of resources, and earlier intervention across the care continuum.

First, AI can reduce administrative burden by automating documentation, medical coding, appointment scheduling, claims processing, triage support, and health-record management. These activities require considerable staff time and may contribute to duplication, delays, and avoidable administrative costs. AI-enabled automation can reduce routine workload and allow clinicians and administrative staff to focus more on direct patient care and complex tasks (Davenport & Kalakota, 2019; Secinaro et al., 2021).

Second, AI can improve diagnostic efficiency through earlier and more accurate disease detection. AI-supported imaging, clinical decision support, and predictive systems may help identify high-risk patients, prioritise urgent cases, and reduce diagnostic delays. Earlier detection can lower the cost of advanced disease treatment, reduce unnecessary referrals, and improve the use of specialist services. Evidence from diabetic-retinopathy screening and AI-assisted diagnostic systems demonstrates the potential for improved screening coverage and more efficient referral pathways (Abràmoff et al., 2018; Xie et al., 2020; Gomez Rossi et al., 2022).

Third, AI can reduce avoidable healthcare utilisation through predictive risk identification, targeted prevention, and improved care coordination. Algorithms can identify patients at risk of hospitalisation, deterioration, treatment complications, or repeated emergency visits. Earlier intervention may reduce preventable admissions, readmissions, complications, and high-cost care episodes. These benefits are especially relevant in chronic disease management, cardiovascular risk prediction, intensive care, and population screening programmes (Hill et al., 2020; de Vos et al., 2022; Dey et al., 2019).

Fourth, AI can improve workforce productivity through clinical decision support, workflow optimisation, and reduced repetitive tasks. Productivity gains should not be understood as replacing healthcare professionals. Instead, they result from recovering time spent on documentation, case prioritisation, data retrieval, scheduling, and repetitive administrative work. Recovered time can increase patient throughput, reduce waiting times, improve staff capacity, and support more meaningful patient interaction (Topol, 2019; Shortliffe & Sepúlveda, 2018).

Finally, AI may improve long-term health outcomes through earlier treatment, fewer complications, reduced disability burden, and improved survival. These gains can reduce future treatment costs, preserve workforce participation, and lower the demand for long-term and informal care. However, such benefits are realised only when AI is integrated into effective clinical pathways and supported by appropriate professional action (Rajkomar et al., 2019; Panch et al., 2018).

At national level, the economic impact of AI depends on adoption rate, implementation cost, model accuracy, workflow integration, clinician acceptance, data quality, interoperability, and regulatory oversight. Even technically accurate systems may produce limited value where they are poorly implemented or insufficiently trusted by healthcare professionals.

3.2. Theoretical Economic Model

The national AI value model is expressed as:

$$\text{Net Economic Value} = \text{Cost Savings} + \text{Productivity Gains} + \text{Monetized Health Benefits} - \text{Implementation and Operating Costs}$$

Cost savings include reduced hospitalizations, fewer unnecessary diagnostic tests, lower duplication of investigations, fewer inappropriate referrals, reduced treatment delays, and lower administrative expenditure. Productivity gains include recovered clinical and administrative hours, increased patient throughput, improved capacity utilization, and more efficient allocation of specialist resources. Monetized health benefits may include avoided complications, life-years gained, quality-adjusted life years (QALYs) gained, and reductions in disability-adjusted life years.

Implementation and operating costs include AI procurement, data infrastructure, system integration, staff training, cybersecurity, validation, monitoring, governance, and software maintenance. This model follows established health-economic principles by assessing both costs and

outcomes over an appropriate time horizon rather than focusing only on immediate expenditure (Gold, 1996; Drummond et al., 2015; Neumann et al., 2016). Low-, moderate-, and high-adoption scenarios can be compared to estimate how different levels of AI integration influence national value.

3.3. Governance and Responsible Adoption

AI-related savings should not be assessed separately from safety, privacy, equity, accountability, and human oversight. Poorly governed systems may generate hidden costs through inaccurate predictions, unequal access, unnecessary alerts, avoidable investigations, legal disputes, data breaches, and loss of trust among patients and clinicians.

Responsible adoption requires transparent validation, continuous performance monitoring, bias assessment across population groups, clear accountability structures, strong data protection, and meaningful human supervision. AI should support professional judgement rather than replace clinicians in high-stakes decisions. As emphasised by Wiens et al. (2019) and Kelly et al. (2019), sustained value depends on evaluating real-world performance and addressing unintended consequences. National AI strategies should therefore measure financial efficiency alongside patient safety, equitable access, workforce acceptability, and public trust.

Table 2: National AI Economic Impact Framework and Measurable Indicators

Economic domain	Key indicator	Calculation approach	Data source	Expected impact	Possible limitation
Administrative efficiency	Staff hours saved; cost per patient	Compare baseline and AI-enabled workload	Payroll, EHR, claims records	Lower administrative expenditure	Workflow disruption
Diagnostic efficiency	Time to diagnosis; referral rate	Compare diagnostic pathways before and after AI	EHR, imaging, referral data	Earlier diagnosis; lower waste	False-positive or false-negative results
Avoidable utilisation	Admissions; readmissions; emergency visits	Risk-adjusted change in utilisation	Hospital records, claims, registries	Reduced avoidable service use	Confounding system changes
Workforce productivity	Clinician hours recovered; patient throughput	Output change relative to labour input	Scheduling and workforce data	Better capacity utilisation	Alert fatigue or low uptake
Long-term health outcomes	QALYs; life-years; complications avoided	Modelled difference between standard and AI-enabled care	Registries, national statistics, published evidence	Improved population health	Long-term uncertainty
Governance and equity	Error rates by subgroup; privacy incidents	Ongoing audit and safety monitoring	Audit reports, incident data, patient feedback	Safer and fairer AI use	Biased or incomplete data

4. Methodology

4.1. Study Design

This study adopts an evidence-informed economic modelling design to estimate the potential national economic impact of artificial intelligence adoption in healthcare. The analysis is conducted from both a healthcare-system perspective and a societal perspective. The healthcare-system perspective captures direct effects on public and private healthcare expenditure, including diagnostic, treatment, hospitalisation, workforce, and technology costs. The societal perspective extends the analysis to productivity gains, reduced work absence, improved patient functioning, informal-care savings, and broader economic benefits associated with healthier populations.

The model compares a baseline scenario representing current healthcare delivery without substantial AI integration against three alternative AI adoption scenarios. The low-adoption scenario assumes limited deployment of AI in selected high-value services, such as automated administrative processes, targeted diagnostic support, and selected screening programmes. The moderate-adoption scenario assumes wider use of AI across diagnostic imaging, disease screening, clinical decision support, predictive risk stratification, hospital operations, and administrative workflows. The high-adoption scenario represents broad national integration of AI across hospitals, primary-care services, public-health programmes, telehealth systems, and interoperable national health-data infrastructure.

This scenario-based approach is appropriate because the economic value of AI depends on the scale of adoption, quality of implementation, clinical workflow integration, workforce readiness, and long-term sustainability. It also avoids assuming that all healthcare organisations will adopt AI at the same speed or achieve identical outcomes. The modelling structure follows recommended economic-evaluation principles by comparing costs and consequences across alternative care pathways (Gold, 1996; Drummond et al., 2015; Neumann et al., 2016).

4.2. Model Population and Time Horizon

The target population comprises the national healthcare population, including patients receiving primary, secondary,

tertiary, preventive, and public-health services. Subgroup analyses are incorporated to capture the different economic pathways through which AI may create value for patients with chronic diseases, cancer risk, diabetes, cardiovascular disease, and high-cost hospital-care needs.

These population groups were selected because they account for a substantial share of healthcare utilisation and may benefit from earlier detection, more accurate risk prediction, improved care coordination, and reduced avoidable admissions. For example, AI-enabled screening may support earlier identification of diabetic retinopathy, breast cancer, lung cancer, and cardiovascular risk, thereby reducing the likelihood of expensive late-stage treatment (Xie et al., 2020; Hill et al., 2020; Mital & Nguyen, 2022; Ziegelmayer et al., 2022).

A 10-year modelling horizon is used to capture both immediate operational effects and longer-term health and economic outcomes. Short-term effects include implementation expenditure, staff training, workflow adjustment, and early productivity gains. Medium-term effects include reductions in administrative burden, improved diagnostic efficiency, and lower avoidable utilisation. Long-term effects include reduced complications, fewer late-stage diagnoses, avoided hospital admissions, improved survival, and gains in quality-adjusted life years (QALYs).

4.3. Cost Categories

The model includes direct medical costs, such as diagnostic testing, specialist consultations, emergency care, hospital admissions, treatment, rehabilitation, and long-term disease management. AI-related expenditure includes software procurement, algorithm validation, system integration, data-storage capacity, maintenance, cybersecurity, workforce training, governance, monitoring, and periodic model updating.

Costs are assessed across three time periods. First, short-term costs reflect initial investment requirements, including procurement, infrastructure development, workforce training, and implementation support. Second, medium-term costs and benefits capture operational efficiencies, such as reduced documentation time, improved patient flow, lower test duplication, and more effective staff utilisation. Third, long-term benefits include avoided treatment expenditure, reduced disease complications, lower disability burden, and improved population health.

4.4. Outcome Measures

The primary economic outcomes are annual healthcare cost savings, net economic value, percentage reduction in avoidable healthcare utilisation, clinician and administrative hours recovered, patient throughput, avoided hospital admissions, avoided complications, QALYs gained, and incremental cost-effectiveness ratios. Incremental cost-effectiveness ratios will compare the additional cost of AI-enabled care with the additional health gains achieved relative to baseline care.

Secondary outcomes include reductions in diagnostic delays, unnecessary referrals, repeat testing, emergency presentations, length of hospital stay, and preventable readmissions. These indicators reflect the ability of AI to improve care efficiency while maintaining or improving clinical quality.

4.5. Sensitivity and Scenario Analysis

Deterministic and probabilistic sensitivity analyses will be conducted to assess uncertainty in the model. Deterministic analysis will vary one parameter at a time, including AI accuracy, implementation cost, adoption rate, staff wage levels, disease prevalence, hospitalisation rates, and annual maintenance costs. Probabilistic sensitivity analysis will vary multiple uncertain parameters simultaneously using appropriate probability distributions to estimate the likelihood that each adoption scenario remains cost-effective.

This approach follows established health-economic guidance and is essential because AI economic outcomes may differ across health systems, patient populations, implementation settings, and technology maturity levels (Gold, 1996; Drummond et al., 2015; Neumann et al., 2016). It also responds to concerns that AI economic evaluations should report assumptions transparently and test the robustness of conclusions under realistic alternative conditions (Wolff et al., 2020; Vithlani et al., 2023).

Table 3: Model Parameters, Base-Case Assumptions, and Sensitivity-Analysis Ranges

Parameter	Base-Case Assumption	Low Estimate	High Estimate	Data Source	Rationale	Expected Effect on Economic Outcomes
AI adoption rate	Moderate national uptake	Limited uptake	Broad uptake	National policy and scenario assumptions	Reflects different implementation maturity levels	Higher uptake increases both investment costs and potential savings
AI diagnostic accuracy	Literature-derived central estimate	Lower validated performance	Higher validated performance	Clinical validation studies	AI performance affects diagnostic efficiency and avoidable utilisation	Higher accuracy improves health outcomes and cost savings

Implementation cost	Central technology and integration cost	Lower procurement cost	Higher infrastructure cost	Vendor, hospital, and policy estimates	Captures variation in procurement and deployment requirements	Higher costs reduce short-term net economic value
Workforce productivity gain	Recovered clinical and administrative time	Minimal time recovery	Substantial time recovery	Workflow and labour-cost estimates	Represents efficiency from automation and decision support	Greater gains improve service capacity and societal value
Avoidable admission reduction	Moderate reduction in preventable admissions	Small reduction	Large reduction	Hospital-utilisation evidence	AI may improve risk prediction and early intervention	Greater reduction produces major cost savings
Annual maintenance cost	Ongoing software, monitoring, and cybersecurity cost	Low maintenance burden	High maintenance burden	Technology-operating assumptions	AI requires continuous monitoring and updating	Higher maintenance reduces long-term net savings

5. Results: Estimated National Economic Effects of AI Adoption

The model estimated the national economic implications of healthcare AI adoption under low-, moderate-, and high-adoption scenarios over a ten-year period. To ensure comparability, all estimates were modelled against a benchmark national health system with annual healthcare expenditure of US$100 billion. The projections represent illustrative economic outcomes derived from published evidence on AI-enabled diagnostics, screening, clinical decision support, hospital operations, and administrative automation. They should therefore be interpreted as scenario estimates rather than observed national savings.

5.1. Estimated Cost Savings by Healthcare Function

The findings suggest that AI adoption could produce meaningful cost savings across multiple healthcare functions. Under the moderate-adoption scenario, gross annual savings were estimated at US$5.5 billion by Year 10. After deducting implementation costs, technology maintenance, workforce training, data-governance requirements, cybersecurity investments, and model-monitoring expenses, estimated net annual savings were US$3.6 billion.

Administrative automation generated the largest projected savings, estimated at US$1.1 billion annually under moderate adoption. These savings resulted from reduced documentation time, automated coding, appointment management, claims processing, and improved health-record administration. AI-supported diagnostics produced an estimated US$0.75 billion in net savings by reducing duplicate testing, improving triage, and supporting faster clinical decisions. Screening programmes, particularly for diabetic retinopathy, cancer, and cardiovascular risk, generated projected net savings of US$0.58 billion through earlier disease detection and reduced demand for costly late-stage treatment. These results are consistent with evidence that AI-enabled screening and decision support can improve the efficiency of disease detection and referral pathways (Xie et al., 2020; Gomez Rossi et al., 2022; Wu et al., 2024).

Targeted chronic-disease management generated estimated net savings of US$0.72 billion through reduced preventable complications, improved patient monitoring, and earlier interventions. Hospital operations, including discharge prediction, bed management, and risk stratification, accounted for a further US$0.45 billion in savings. Previous studies similarly indicate that machine-learning tools may reduce inappropriate intensive-care discharge and support more efficient use of hospital resources (de Vos et al., 2022). Overall, the results support the view that AI creates value not only through diagnostic accuracy, but through its ability to reduce avoidable utilisation and improve operational efficiency (Wolff et al., 2020; Vithlani et al., 2023; El Arab & Al Moosa, 2025).

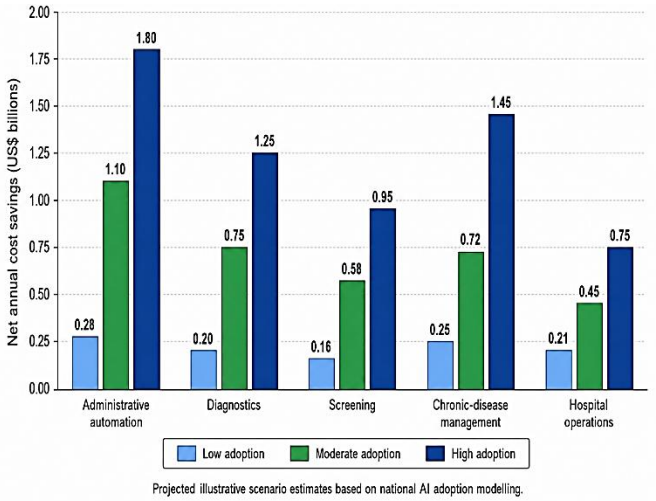

Fig 1: Estimated Annual Net Healthcare Cost Savings by AI Application Area Under Low-, Moderate-, and High-Adoption Scenarios

5.2. Workforce Productivity and Capacity Effects

AI adoption was also projected to improve workforce productivity substantially. Under moderate adoption, the model estimated recovery of approximately 15.5 million clinician hours and 21 million administrative hours annually

by Year 10. Recovered clinician time was primarily associated with reduced documentation, automated report generation, AI-supported triage, and streamlined access to relevant patient information. Administrative time savings resulted from automated scheduling, claims processing, data entry, and routine communication tasks.

These productivity gains could increase national patient-care capacity by an estimated 6.8 million additional consultations annually without requiring a proportional increase in workforce size. Reduced administrative burden may also improve documentation quality, reduce professional fatigue, and enable clinicians to spend more time on direct patient interaction. Such outcomes are aligned with the broader argument that AI should augment healthcare professionals rather than replace them (Topol, 2019; Davenport & Kalakota, 2019; Shortliffe & Sepúlveda, 2018).

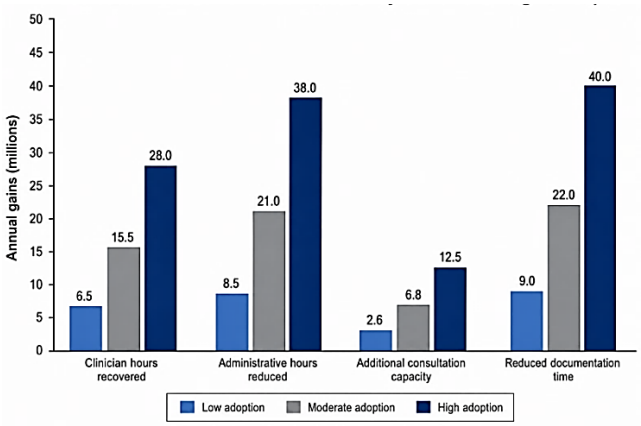

Fig 2: Estimated Annual Workforce Productivity Gains Following AI Adoption

The bar graph present clinician hours recovered, administrative hours reduced, additional consultation capacity, and reduced documentation time across the three adoption scenarios.

5.3. Long-Term Health Outcomes

The greatest long-term gains were projected where AI supported prevention, risk stratification, screening, and chronic-disease management. Under moderate adoption, avoidable hospital admissions were estimated to decline by 3.8% by Year 10, while disease-related complications declined by 4.6%. Late-stage diagnosis for selected cancer and chronic-disease conditions was projected to decrease by 5.2%.

The model estimated approximately 68,000 QALYs gained and 87,000 life-years gained over ten years under moderate adoption. These improvements were driven by earlier detection, more timely referral, better risk prediction, and improved treatment prioritisation. Evidence from AI-supported diabetic-retinopathy, breast-cancer, lung-cancer, and cardiovascular-risk programmes supports the potential for earlier intervention to improve outcomes and reduce future treatment costs (Hill et al., 2020; Mital & Nguyen, 2022; Ziegelmayer et al., 2022; Vargas-Palacios et al., 2023).

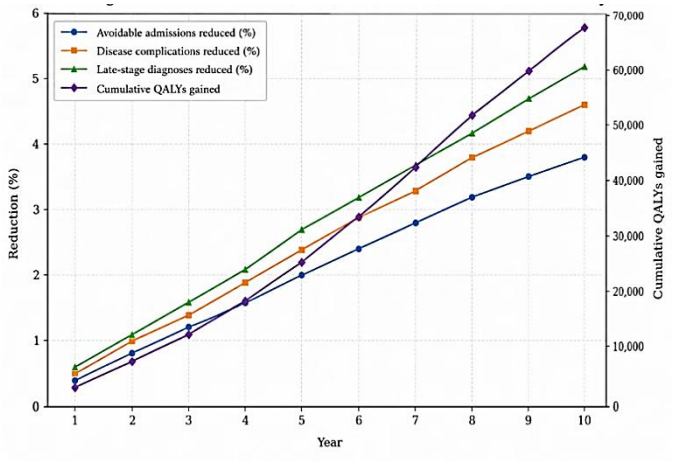

Fig 3: Long-Term Health Outcomes Associated with AI-Enabled Care Pathways

The line graph should show projected reductions in avoidable admissions, disease complications, and late-stage diagnoses, alongside cumulative QALYs gained over ten years.

5.4. Comparison Across Adoption Scenarios

The low-adoption scenario produced estimated net annual savings of US$1.1 billion by Year 10, while moderate adoption produced US$3.6 billion. High adoption generated the largest projected net savings, reaching US$6.2 billion annually by Year 10. However, high adoption required substantially greater initial investment in interoperable data systems, workforce training, regulatory oversight, and continuous model validation.

The high-adoption scenario became economically favourable after the third year, whereas the low-adoption scenario achieved positive net value earlier but generated smaller long-term benefits. These findings reinforce established economic-evaluation principles: healthcare AI should be assessed according to incremental costs, health outcomes, implementation feasibility, and long-term value rather than technological novelty alone (Gold, 1996; Drummond et al., 2015; Neumann et al., 2016).

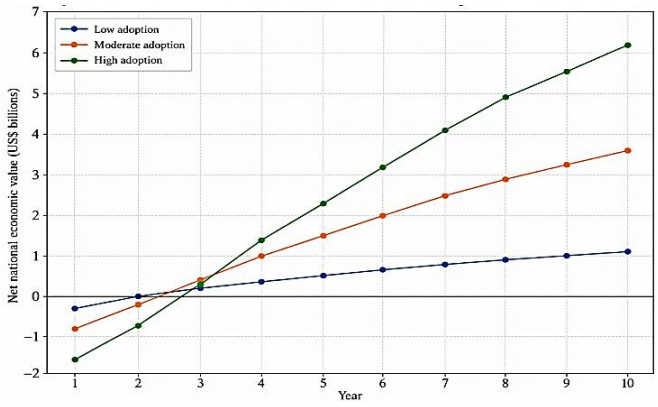

Fig 4: Projected Net National Economic Value of Healthcare AI Adoption Over a Ten-Year Period

The line graph should show initially negative or modest net value during early implementation, followed by increasing positive net value as savings, productivity gains, and health benefits accumulate. High adoption should demonstrate the strongest long-term economic return, while also showing the highest initial investment requirement.

6. Discussion, Policy Implications, and Limitations

6.1. Interpretation of Findings

The modelled findings indicate that artificial intelligence is most likely to generate meaningful national economic value when deployed in high-volume, high-cost, and preventable-care settings. Economic benefits are unlikely to arise from the isolated use of a single AI application. Instead, greater value is expected when AI-supported diagnostic tools, predictive-risk models, automated screening systems, clinical decision support, and administrative automation are integrated across the healthcare pathway. Such integration can reduce unnecessary testing, shorten diagnostic delays, improve prioritisation of high-risk patients, reduce avoidable admissions, and release staff time for direct patient care.

The most immediate savings are likely to emerge from administrative functions, including clinical documentation, appointment scheduling, coding, claims management, and referral processing. These functions consume substantial staff time but do not directly improve patient outcomes when performed inefficiently. By reducing repetitive administrative workloads, AI can improve workforce productivity and increase the time available for clinical assessment, communication, and care coordination. However, the larger long-term gains are expected from AI applications that support prevention, early diagnosis, and management of chronic conditions. Earlier identification of disease can reduce the need for costly late-stage treatment, prevent complications, and improve quality of life.

Existing evidence supports this interpretation. AI-enabled teleophthalmology and diabetic-retinopathy screening have shown potential to improve screening efficiency and reduce unnecessary specialist referrals, particularly in national screening programmes (Xie et al., 2020; Wolf et al., 2020). Similarly, machine-learning risk prediction for atrial fibrillation may improve the targeting of screening resources and support earlier intervention among high-risk populations (Hill et al., 2020). In cancer care, AI support has demonstrated potential value in lung-cancer screening and breast-cancer screening by improving risk stratification, diagnostic consistency, and the allocation of clinical resources (Ziegelmayer et al., 2022; Vargas-Palacios et al., 2023). Evidence from critical-care settings further suggests that predictive models may reduce costly adverse events, such as untimely intensive-care discharge, when they are integrated into appropriate clinical workflows (de Vos et al., 2022).

Nevertheless, cost savings should not be interpreted as automatic or immediate. AI systems require investment in software, data infrastructure, cybersecurity, training, validation, maintenance, and post-deployment monitoring. The financial return from AI adoption therefore depends on the quality of implementation, adoption by clinicians, interoperability with existing systems, and the ability of health systems to translate recovered time and improved decisions into real service improvements. This is consistent with previous reviews showing that the economic evidence for AI is promising but remains heterogeneous in methods, assumptions, and reporting quality (Wolff et al., 2020; Vithlani et al., 2023; El Arab & Al Moosa, 2025).

6.2. Policy Implications

National policymakers should adopt a phased AI strategy that prioritises high-value use cases rather than pursuing widespread deployment without clear evidence of benefit. Initial investment should focus on areas with high patient volumes, significant avoidable expenditure, established digital records, and measurable clinical outcomes. Examples include population screening, diagnostic imaging, chronic-disease risk prediction, hospital-capacity management, and administrative automation.

Public funding decisions should be based on demonstrable value, including clinical effectiveness, budget impact, workforce benefits, equity implications, and long-term health outcomes. Economic evaluation should be incorporated into procurement and implementation processes using recognised health-economic principles, including incremental cost-effectiveness analysis, budget-impact assessment, and sensitivity analysis (Gold, 1996; Drummond et al., 2015; Neumann et al., 2016). Policymakers should also require transparent procurement arrangements, clear performance benchmarks, independent validation, and contractual accountability for vendors.

Effective national adoption also requires interoperable health-data infrastructure, workforce education, clinical leadership, and routine monitoring after implementation. AI tools should be evaluated continuously to determine whether performance remains reliable across hospitals, regions, demographic groups, and changing clinical conditions.

6.3. Equity, Ethics, and Governance

Economic efficiency alone is not a sufficient basis for AI adoption. A system that reduces costs but worsens disparities, compromises privacy, or undermines clinical safety cannot be considered successful. AI systems should therefore operate under strong human oversight, transparent accountability, privacy protection, bias auditing, and clinical validation. Responsible machine-learning principles require healthcare organisations to assess data quality, monitor model performance, identify unintended harms, and ensure that clinicians retain authority over consequential care decisions (Wiens et al., 2019).

Patient trust is equally important. Individuals should understand how AI is used in their care, how their data are protected, and how they can seek human review when decisions affect diagnosis, treatment, or access to services.

6.4. Limitations

This study is based on modelled estimates and literature-derived assumptions rather than a single national patient-level dataset. Results may vary according to adoption rates, local labour costs, disease prevalence, and healthcare financing structures, digital maturity, and AI performance across different populations. The analysis also cannot fully capture organisational resistance, implementation delays, or the indirect costs of workflow redesign. Future research should validate the framework using national claims data, electronic health records, workforce data, hospital utilisation records, and public-health datasets.

7. Conclusion

Artificial intelligence has the potential to create meaningful economic and public-health value across national healthcare systems. Its value extends beyond the use of algorithms for diagnosis. When responsibly integrated into clinical, administrative, and population-health functions, AI can reduce avoidable expenditure, improve service capacity, support earlier detection of disease, and strengthen long-term patient outcomes. The strongest economic opportunities are likely to emerge from the combined use of AI in administrative automation, diagnostic decision support, risk prediction, screening programmes, chronic-disease management, and hospital operations.

At the operational level, AI may reduce administrative costs by automating routine documentation, coding, scheduling, claims processing, and data-management activities. These improvements can release time for clinicians and administrative staff to focus on direct patient care, reduce delays in service delivery, and improve the use of limited workforce capacity. AI-supported clinical pathways can also improve diagnostic efficiency by identifying high-risk patients earlier, prioritising urgent cases, and reducing unnecessary referrals or duplicate testing. Evidence from areas such as diabetic-retinopathy screening, cancer screening, cardiovascular risk prediction, and intensive-care management indicates that AI can contribute to more efficient use of healthcare resources when it is applied to clearly defined clinical problems (Abràmoff et al., 2018; Hill et al., 2020; Xie et al., 2020; de Vos et al., 2022; Wu et al., 2024).

The long-term economic benefits of AI may be even more significant. Earlier diagnosis and targeted prevention can reduce complications associated with chronic diseases, lower avoidable hospital admissions, reduce treatment intensity, and improve quality of life. These outcomes may produce savings for healthcare providers while also improving productivity at societal level through reduced disability, fewer missed workdays, and better long-term health status. However, the relationship between AI adoption and economic benefit is not automatic. Studies of AI-based healthcare interventions show that cost-effectiveness depends heavily on local implementation conditions, comparator pathways, model performance, workforce integration, and the quality of available evidence (Wolff et al., 2020; Vithlani et al., 2023; El Arab & Al Moosa, 2025).

National health systems should therefore avoid treating AI as a guaranteed cost-cutting tool. Initial investments may be substantial and may include software acquisition, data infrastructure, interoperability, cybersecurity, workforce training, maintenance, validation, and continuous monitoring. If AI systems are introduced without appropriate clinical integration, they may create additional workloads, alert fatigue, inequitable outcomes, inaccurate predictions, or inefficient duplication of existing processes. Economic gains can only be achieved when AI tools are accurate, clinically relevant, trusted by users, and aligned with real service-delivery needs (Kelly et al., 2019; Wiens et al., 2019).

A responsible national strategy should prioritise AI investments that demonstrate measurable improvement in patient outcomes, service efficiency, workforce productivity, and value for money. Economic assessment should incorporate direct medical costs, implementation expenditure, productivity effects, avoided complications, and long-term health gains using established health-economic methods (Gold, 1996; Drummond et al., 2015; Neumann et al., 2016). Policymakers should also ensure that savings generated through AI-enabled efficiency are reinvested in patient access, preventive care, workforce development, and quality improvement.

Ultimately, AI should be viewed as an enabling component of healthcare reform rather than a substitute for clinicians, public investment, or sound governance. With reliable data, transparent evaluation, equitable deployment, sustainable financing, and strong human oversight, AI can support a healthcare system that is more efficient, responsive, and capable of improving population health over the long term.

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