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Economic evaluation of AI-assisted technologies in healthcare: A systematic review

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Abstract

Artificial intelligence (AI) technologies are increasingly integrated into healthcare, yet their economic value remains uncertain. Traditional economic evaluation methods may not adequately capture the unique features of AI, including dynamic model evolution, scalability, and broader societal impacts. This systematic review synthesized existing evidence on the cost-effectiveness of AI-based healthcare interventions and assessed the methodological rigor of published studies. A comprehensive search identified health economic evaluations of AI applications published between September 2019 and March 2025, following PRISMA and SWiM guidelines and registered in PROSPERO (CRD42025641230). Eligible studies were full economic evaluations comparing AI-based interventions with non-AI alternatives, and data were extracted on study characteristics, analytical methods, decision-analytic models, perspectives, outcomes, and AI-specific costs. Methodological quality was evaluated using the CHEERS checklist. A total of 52 studies from 15 countries were included, most published after 2020, focusing on diabetic retinopathy screening, cancer detection, and cardiovascular disease applications. Cost-utility analysis was the predominant method (79%), followed by cost-effectiveness analysis (15%). Nearly all studies (98%) concluded that AI-based strategies were cost-effective, cost-beneficial, or cost-saving. However, reporting of AI-specific costs was inconsistent, while over 90% of studies detailed expenses such as software licensing, per-test charges, or maintenance fees, some omitted cost information entirely, limiting comparability. Overall, AI-based healthcare interventions are generally reported as cost-effective, but methodological heterogeneity, incomplete cost reporting, and potential publication bias constrain the reliability and comparability of current evidence. Standardized economic evaluation frameworks that incorporate comprehensive cost structures and account for the evolving nature of AI are urgently needed.

Keywords: Artificial intelligence, Economic evaluation, Systematic review, Software as medical device

1. Introduction

Healthcare systems worldwide face growing pressures from rising costs, limited budgets, and increasing patient demand. Within this context, artificial intelligence (AI) technologies have rapidly emerged as potential solutions across a wide range of healthcare settings. AI is being applied to diagnostics [1], treatment planning [2], predictive analytics [3], facilitate screening [4], among other uses. By leveraging large datasets, AI can support more efficient clinical decision-making and improve the quality and delivery of care [5,6].

Given finite healthcare resources, it is essential to evaluate not only clinical effectiveness but also the economic value of emerging technologies. Economic evaluations, such as cost-effectiveness and cost-utility analyses, systematically compare costs and health outcomes to guide healthcare policy, reimbursement decisions, and resource allocation.

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These evaluations typically use incremental cost-effectiveness ratios (ICERs) and quality-adjusted life years (QALYs) to quantify value [7].

Economic evaluations of AI-assisted technologies, however, face methodological challenges that differ from those of pharmaceuticals. Unlike drugs, which have well-defined comparators and remain fixed after approval, AI interventions are dynamic and evolve with user feedback, requiring ongoing clinician engagement. They are often deployed at scale with marginal costs approaching zero, and their benefits may extend beyond health outcomes to include productivity gains and other societal effects [8−10]. In addition, the high technical complexity and versatility of AI complicate its evaluation with standard cost-effectiveness methods. Traditional cost-per-QALY analyses may therefore be insufficient to capture the broader impact of AI, highlighting the need for tailored methodological approaches [8].

The existing literature on the economic evaluation of AI technologies shows substantial variability in methodological rigor and comprehensiveness [11−13]. Many studies emphasize technical performance or short-term predictive accuracy rather than long-term, patient-centered outcomes or cost-effectiveness measures relevant to healthcare decision-makers. Furthermore, critical components of robust economic evaluation, such as comprehensive uncertainty analyses and transparent interpretation of ICERs, are frequently lacking [8]. Despite the rapid growth of AI-related clinical research, rigorous and comprehensive economic evaluations remain relatively scarce [11,13].

In light of these methodological complexities, this systematic review aims to synthesize current evidence on economic evaluations of AI-assisted healthcare technologies. Specifically, we seek to identify, evaluate, and summarize existing studies, highlighting methodological strengths and limitations. We also aim to clarify key challenges in conducting such evaluations and to identify gaps and opportunities for advancing this field.

2. Methods

We conducted a systematic review of health economic evaluations (HEEs) of AI applications in healthcare, focusing on full economic evaluations that compared both costs and consequences of AI-based interventions. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) and the Synthesis Without Meta-analysis (SWiM) guidelines [14,15], and the protocol was registered on PROSPERO (registration number: CRD42025641230).

2.1. Search strategy

A comprehensive literature search was conducted in PubMed, covering the period from September 2019 through March 2025. The objective was to identify original studies evaluating the cost-effectiveness of AI in clinical healthcare settings. The search was performed without restrictions on language, study design, or country. Search terms combined Medical Subject Headings (MeSH) and free-text keywords related to artificial intelligence ("artificial intelligence," "machine learning," "deep learning") with terms related to economic evaluation ("cost-effectiveness," "cost-utility," "cost-benefit," "economic evaluation"). Boolean operators (AND, OR) were used to structure the search. The detailed search strategy is provided in Supplementary Table S1 (https://doi.org/10.38212/2224-6614.3570).

2.2. Eligibility criteria

Studies were eligible for inclusion if they met the following criteria, based on the PICO framework: (i) Population: patients receiving clinical care in any healthcare setting (e.g., primary care, tertiary care, national screening programs); (ii) Intervention/Comparator: at least one comparator involving AI-based intervention and a non-AI alternative (e.g., standard care, human expert, or traditional diagnostics); (iii) Outcome: at least one full economic evaluation outcome, including cost-effectiveness (e.g., cost per QALY, cost per case detected), cost-utility, cost-benefit, or cost-minimization metrics. Only full economic evaluations were included. Studies reporting only cost analysis, simulation-only models without real-world comparators, or economic reviews were excluded.

2.3. Data extraction

A standardized data extraction form was used to collect study-level information. Two reviewers (WTW and YWC) independently extracted the following data for each study: author, year of publication, country, clinical domain, type of AI product, study objective, comparator, type of economic evaluation, model type, perspective, primary outcomes, and AI-specific cost elements (e.g., per-use cost, development cost). Discrepancies in data extraction were resolved by consensus, and a third reviewer (PHH) adjudicated disagreements when necessary.

2.4. Assessment of methodological quality

The quality of the included studies was assessed using the Consolidated Health Economic Evaluation Reporting Standards (CHEERS) checklist [16]. The CHEERS statement evaluates the completeness of HEEs across 28 items in 7 domains.

3. Results

3.1. Study selection

The search identified 4083 records. After removing 1367 duplicates, 2716 records remained for screening by title and abstract. Most were excluded for irrelevance (e.g., not related to AI, not a health economic evaluation, or not a journal article). Fifty-six reports were assessed in full text, and three were excluded for not evaluating AI in a health economic context. In total, 52 studies were included in the review (Fig. 1).

3.2. General characteristics

The 52 included studies were conducted across 15 countries. The United States contributed the largest number (n = 17), followed by China (n = 13) and the United Kingdom (n = 5). Other countries with multiple studies included Germany (n = 4), Australia (n = 3), and Sweden (n = 2). Single studies were reported from Singapore, Ireland, the Netherlands, Canada, Italy, Denmark, Israel, Japan, Spain, and Taiwan. Publication activity has accelerated in recent years, with the majority of studies appearing between 2022 and 2025 (n = 36, 69%), reflecting growing global attention to the economic evaluation of AI in healthcare.

Ophthalmology was the most frequently represented (n = 14, 27%), largely focused on diabetic retinopathy, retinopathy of prematurity, and cataract screening. Oncology accounted for 11 studies (21%), including colorectal cancer detection during colonoscopy, lung cancer screening and risk prediction, early gastric cancer detection, and prostate cancer pathology. Cardiovascular diseases were examined in 7 studies (13%), covering applications such as AI-ECG for atrial fibrillation and left ventricular dysfunction, chest pain risk stratification, opportunistic CT screening for CVD, and prenatal ultrasound for congenital heart disease. Other domains included infectious diseases (n = 3, 6%; tuberculosis and sepsis), neurology and intensive care (n = 3, 6%; stroke detection, ICU discharge and ventilation), and a diverse group of miscellaneous areas (n = 14, 27%) such as dentistry, rehabilitation, fall prevention, nutrition diagnostics, obstetrics, and musculoskeletal health.

In terms of technology, most studies evaluated device-integrated systems (n = 36, 69%), reflecting the predominance of AI tools embedded into imaging, diagnostic, and monitoring equipment. Pure algorithms (n = 11, 21%) were mainly applied for predictive modeling and population-level screening tasks. A smaller number assessed interactive apps (n = 2, 4%) designed for treatment adherence or self-management, decision-support software (n = 1, 2%) for intrapartum monitoring, and ICU-focused decision tools (n = 2, 4%) used for discharge and ventilation management. This distribution shows that economic evaluations of AI have concentrated on hardware-integrated diagnostic systems, while a minority have explored software-only or app-based approaches.

The studies were conducted in varied healthcare settings. Most evaluations focused on national or regional screening programs (e.g., diabetic retinopathy, breast cancer, cervical cancer) or tertiary care centers. A smaller number assessed AI in critical care [17,18], community screening program [19], or community-based care models in low- and middle-income countries [20]. This diversity highlights the broad and expanding interest in evaluating AI across different healthcare contexts and the growing emphasis on assessing its economic value using structured methods. Detailed characteristics are presented in Table 1.

3.3. Health economic characteristics

Most studies applied cost-utility analysis (n = 37, 78.7%), followed by cost-effectiveness analysis (n = 7, 14.9%). Only one study each used cost-consequence analysis [21], cost-benefit analysis [22], and cost-minimization analysis [23] (2.1% each). The majority employed decision-analytic modeling, with Markov models the most common (n = 24, 51.1%), followed by hybrid models combining decision trees and Markov models (n = 10, 21.3%) and decision trees alone (n = 9, 19.1%). A few studies applied alternative modeling approaches (n = 3, 6.4%).

Regarding perspective, nearly half of the studies adopted a healthcare system perspective (n = 21, 44.7%). Societal perspectives were reported in 12 studies (25.5%), while payer perspectives were used in 6 studies (12.8%). A smaller number reported combined perspectives, including societal and healthcare system (n = 6, 12.8%), and payer and employer (n = 1, 2.1%). Only one study (2.1%) adopted a patient perspective. This diversity

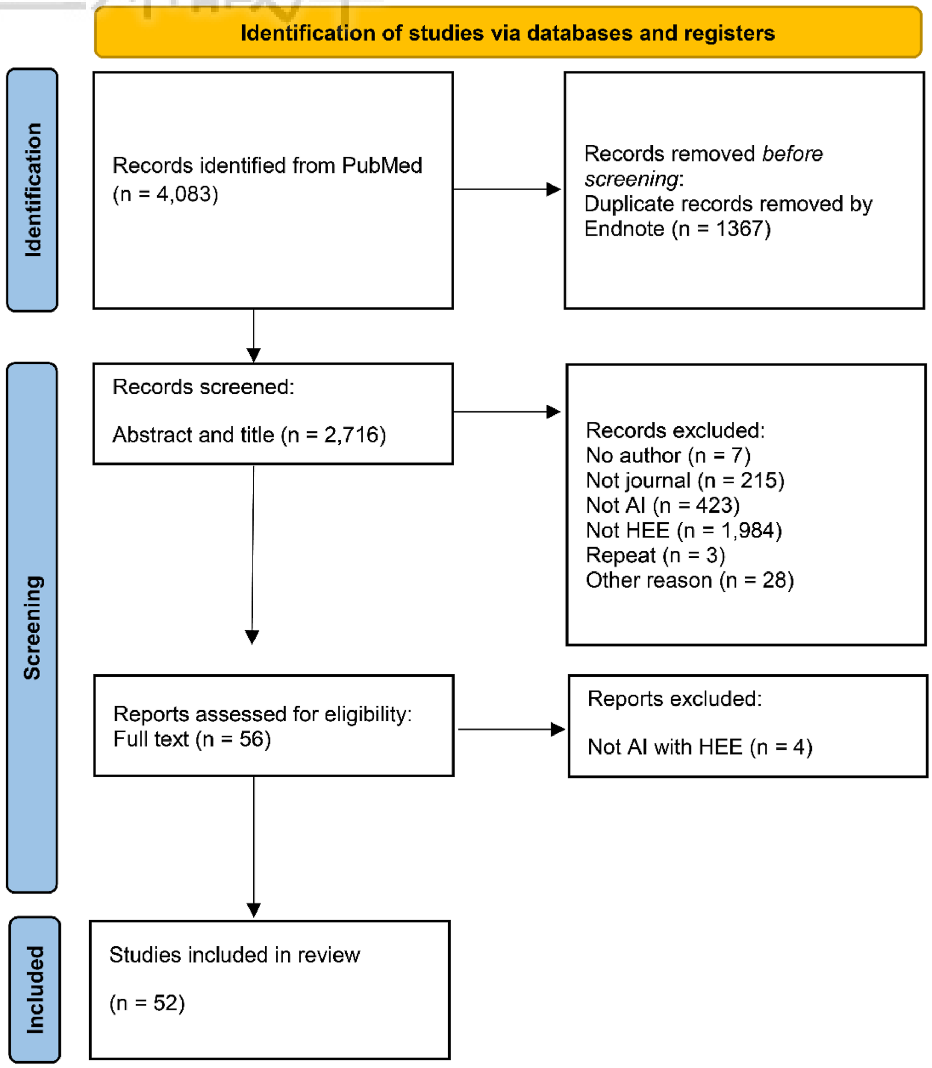

Fig. 1. PRISMA flow diagram of systematic review process.

highlights increasing interest in assessing AI not only from a healthcare or payer viewpoint but also from broader societal and patient-centered perspectives.

Across all studies, 98.1% (n = 51) concluded that AI-based strategies were cost-effective, cost-beneficial, or cost-saving. One study reported conditional outcomes, stating that AI was "potentially cost-effective" depending on modeling assumptions or specific scenarios [24].

AI implementation costs varied substantially across the included studies. Pricing models commonly involved per-test charges (n = 20, 42.6%), combinations of licensing, per-test, and maintenance fees (n = 10, 21.3%), or software licensing alone (n = 5, 10.6%). Smaller numbers of studies reported licensing with per-test fees (n = 4, 8.5%) or licensing with maintenance fees (n = 2, 4.3%), while a few reported only maintenance fees (n = 1, 2.1%) or per-test with maintenance fees (n = 1, 2.1%). Importantly, 4 studies (8.5%) did not specify any cost details, which limits transparency and comparability.

In screening applications, costs were often reported on a per-test basis, ranging from a few dollars for chest X-ray or ECG interpretation [19,25,26] o around $60 per patient annually for AI-supported programs [23]. Treatment monitoring solutions sometimes adopted a per-patient structure, with costs reaching several thousand dollars per year for AI-enabled tuberculosis adherence support [27]. Diagnostic applications showed even greater variation, with image-based assessments ranging from tens of euros per case to several hundred euros per correct diagnosis [28,29]. More complex AI platforms, such as mammography or critical care

Table 1. General characteristics.

Author	Year	Country	Objective	Type of AI
Padula, W. V. et al. [36]	2019	USA	Cost-utility of repeated risk assessments for pressure injury prevention	Pure algorithm
van Wyk, F. et al. [22]	2019	USA	Cost-benefit of ML-based acquisition systems for sepsis	Device-integrated system
Hill, N. R. et al. [37]	2020	UK	Cost-effectiveness of ML-guided targeted screening for atrial fibrillation	Pure algorithm
Wolf, R. M. et al. [38]	2020	USA	Cost-effectiveness of AI screening for diabetic retinopathy in pediatric diabetes	Device-integrated system
Xie, Y. et al. [23]	2020	Singapore	Cost-minimization of deep learning versus human assessment for diabetic retinopathy screening	Pure algorithm
Schroeder, E. et al. [21]	2020	UK and Ireland	Economic evaluation of AI-assisted cardiotocography interpretation during labor	Decision-support software
Nsengiyumva, N. P. et al. [19]	2021	Pakistan	Cost-effectiveness of AI-based chest X-ray triage strategies for pulmonary tuberculosis diagnosis	Device-integrated system
Salcedo, J. et al. [27]	2021	USA	Cost-effectiveness of AiCure for AI-based treatment monitoring of active tuberculosis	Interactive app
Schwendicke, F. et al. [39]	2021	Germany	Cost-effectiveness of AI-assisted proximal caries detection on bitewing radiographs	Device-integrated system
Tseng, A. S. et al. [40]	2021	USA	Cost-effectiveness of AI-ECG algorithm for universal screening of asymptomatic left ventricular dysfunction	Pure algorithm
van Leeuwen, K. G. et al. [24]	2021	UK	Cost-effectiveness of AI for large vessel occlusion detection in acute ischemic stroke	Device-integrated system
Mallow, P. J. et al. [41]	2021	USA	Cost-utility of OUDTEST for predicting opioid use disorder in orthopedic surgical patients	Pure algorithm
Areia, M. et al. [42]	2022	USA	Cost-effectiveness of AI detection tools in screening colonoscopy for colorectal cancer prevention	Device-integrated system
de Vos, J. et al. [17]	2022	Netherlands	Cost-effectiveness of Pacmed Critical for ICU discharge decision-making	Software
Ericson, O. et al. [43]	2022	Sweden	Cost-effectiveness of ML algorithm for sepsis detection in ICUs	Pure algorithm
Fuller, S. D. et al. [44]	2022	USA	Cost-effectiveness of ARIAS-based diabetic retinopathy screening in low-income primary care	Device-integrated system
Gomez Rossi, J. et al. [45]	2022	USA	Cost-effectiveness of AI for clinician support in dermatology, dentistry, and ophthalmology	Device-integrated system
Huang, X. M. et al. [46]	2022	China	Cost-effectiveness of AI screening for diabetic retinopathy	Device-integrated system
Mital, S. and H. V. Nguyen [30]	2022	USA	Cost-effectiveness of AI versus PRS risk-stratified mammography screening	Device-integrated system

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Table 1. (continued)

Author	Year	Country	Objective	Type of AI
Morrison, S. L. et al. [47]	2022	USA	Cost-effectiveness of autonomous and assistive AI-based ROP screening	Device-integrated system
Ziegelmayer, S. et al. [48]	2022	USA	Cost-effectiveness of AI in initial CT scans for lung cancer screening	Device-integrated system
Schwendicke, F. et al. [29]	2022	Germany	Cost-effectiveness of AI-supported detection of proximal caries	Device-integrated system
Barkun, A. N. et al. [49]	2023	Canada	Cost-effectiveness of AI-aided colonoscopy using GI Genius	Device-integrated system
Hassan, C. et al. [50]	2023	Italy	Cost-utility of GI GENIUS AI system in colonoscopy for FIT-positive patients	Device-integrated system
Li, H. et al. [51]	2023	China	Cost-effectiveness of AI-based diabetic retinopathy screening vs ophthalmologist and no screening	Device-integrated system
Lin, S. et al. [20]	2023	China	Cost-effectiveness of AI-assisted DR telemedicine vs manual grading in LMICs	Device-integrated system
Liu, H. et al. [52]	2023	China	Cost-effectiveness of screening methods for major blindness-causing eye diseases	Device-integrated system
Pham, C. T. et al. [53]	2023	Australia	Cost-effectiveness and value of information of AmbIGeM AI system for fall prevention	Device-integrated system
Pickhardt, P. J. et al. [54]	2023	USA	Cost-effectiveness of AI-assisted opportunistic CT screening for CVD, osteoporosis, and sarcopenia	Device-integrated system
Shen, M. et al. [25]	2023	China	Cost-effectiveness of AI-assisted LBC vs manual LBC and HPV testing for cervical cancer	Device-integrated system
Srisubat, A. et al. [55]	2023	Thailand	Cost-utility of DL vs human graders in Thailand's DR screening	Pure algorithm
Chawla, H. et al. [56]	2023	USA	Cost-effectiveness of fully automated retinal image screening vs universal ophthalmologist referral	Device-integrated system
Curl, P. K. et al. [57]	2024	USA	Cost-effectiveness of AI-based opportunistic screening for vertebral fractures	Device-integrated system
Ginsberg, G. M. et al. [58]	2024	Israel	Cost-utility of DL-assisted ultrasound in prenatal screening for congenital heart disease	Device-integrated system
Hill, H. et al. [59]	2024	UK	Cost-effectiveness of AI-based risk-stratified vs age-based breast cancer screening	Device-integrated system
Hu, W. et al. [60]	2024	Australia	Cost-effectiveness of AI-based diabetic retinopathy screening vs current clinical practice	Device-integrated system
Kongstad, L. P. et al. [61]	2024	Denmark	Cost-effectiveness of AI-based selfBACK app for low back pain management	Interactive app
Lin, S. et al. [62]	2024	China	Cost-effectiveness and cost-utility of AI-assisted community-based fundus screening	Device-integrated system

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Table 1. (continued)

Author	Year	Country	Objective	Type of AI
Liu, W. T. et al. [26]	2024	Taiwan	Cost-effectiveness of AI-ECG for asymptomatic left ventricular dysfunction	Pure algorithm
Marka, A. W. et al. [63]	2024	USA	Cost-effectiveness of AI support in MR imaging for renal lesion classification	Device-integrated system
Sun, M. Y. et al. [64]	2024	China	Cost-effectiveness of AI-based rapid nutritional diagnostic system in hospitals	Device-integrated system
Tsiachristas, A. et al. [65]	2024	UK	Cost-effectiveness of AI-Risk for CV risk management in chest pain patients	Device-integrated system
Wang, Y. et al. [66]	2024	China	Impact of AI model sensitivity/specificity on cost-effectiveness of DR screening	Pure algorithm
Wu, X. et al. [67]	2024	China	Cost-effectiveness and cost-utility of digital hierarchical screening for cataract detection	Device-integrated system
Yonazu, S. et al. [33]	2024	Japan	Cost-effectiveness of AI-assisted CADx (Tango) for early gastric cancer detection	Device-integrated system
Zanghelini, F. et al. [68]	2024	UK	Cost-effectiveness of GaitSmart AI rehab tool after joint replacement	Device-integrated system
Zwerwer, L. R. et al. [18]	2024	Germany	Early-stage cost-effectiveness of AI in ICU mechanical ventilation	Device-integrated system
Ahmed, M. et al. [69]	2025	USA	Cost-effectiveness of autonomous AI screening for pediatric diabetic retinal disease	Device-integrated system
Akune, Y. et al. [32]	2025	Japan	Cost-effectiveness of AI DR screening in Japan? SHC and diabetes management	Device-integrated system
Du, X. et al. [28]	2025	Sweden	Cost-effectiveness and effectiveness of AI-assisted prostate cancer pathology	Device-integrated system
Trujillo, J. C. et al. [31]	2025	Spain	Cost-effectiveness of LungFlag ML risk prediction for lung cancer screening	Pure algorithm
Huang, F. et al. [70]	2025	China	Cost-effectiveness of mobile AI-integrated low-dose CT lung cancer screening	Device-integrated system

Abbreviations: AI, artificial intelligence; CADx, computer-aided diagnosis; CT, computed tomography; CVD, cardiovascular disease; DL, deep learning; DR, diabetic retinopathy; ECG, electrocardiogram; FIT, fecal immunochemical test; HPV, human papillomavirus; ICU, intensive care unit; LBC, liquid-based cytology; LMIC, low- and middle-income country; ML, machine learning; PRS, polygenic risk score; ROP, retinopathy of prematurity; SHC, special health checkups.

decision-support systems, incurred substantial fixed development costs exceeding $60,000, along with recurring annual license fees in the tens of thousands [30,31]. At the population level, investments could reach tens of thousands of dollars per case prevented or hundreds of millions for national-scale deployment [32,33]. Detailed health economic characteristics are presented in Table 2.

3.4. Methodological quality of included studies

Overall, the methodological quality of the 52 included studies was rated as good according to the CHEERS checklist. Detailed performance across all items is provided in Supplementary Table S2 and Supplementary Figure S1 (https://doi.org/10.38212/2224-6614.3570). Four items showed suboptimal reporting, with fewer than half of the studies addressing them adequately: presence of a health economic analysis plan, characterization of distributional effects, description of approaches to patient and stakeholder engagement, and assessment of the effects of such engagement.

4. Discussion

This systematic review synthesized the most recent evidence from 52 economic evaluations of AI applications in healthcare published between 2019

Table 2. Health economic characteristics.

Author	Setting	Primary outcome	Perspective	HEE type	DAM type	Comparator	Type of AI cost
Padula, W. V. et al.	Tertiary care	ICER per QALY gained	Societal and health care system perspectives	CUA	Markov model	Standard care	Not specified
van Wyk, F. et al.	Tertiary care/ICU	Cost-benefit of machine learning applied to early detection of sepsis	Societal perspective	CBA	Decision tree	Standard care	Maintenance fees
Hill, N. R. et al.	Primary care	ICER per QALY gained	Health care system	CUA	Decision tree and Markov model	No AI	Not specified
Wolf, R. M. et al.	Primary care	Incremental cost per additional diabetic retinopathy case detected	Patient's perspective	CEA	Decision tree	Standard care	Per-test charges
Xie, Y. et al.	National screening program	Total cost per patient screened across different AI-based models	Health care system	CMA	Decision tree	Standard care	Per-test charges/ Maintenance fees
Schroeder, E. et al.	Secondary care	Composite poor neonatal outcome and developmental progress at age 2	Health care system	CCA	NA	Standard care	Not specified
Nsengiyumva, N. P. et al.	Community screening program	Costs and DALY averted	Health care system	CEA	Decision tree	Standard care	Per-test charges
Salcedo, J. et al.	Community-based care	ICER per QALY gained	societal perspective	CUA	Markov model	Standard care	Software licensing/ Maintenance fees
Schwendicke, F. et al.	Primary care	Incremental cost per gained year of tooth retention	Health care system	CEA	Markov model	Standard care	Per-test charges
Tseng, A. S. et al.	Tertiary care	ICER per QALY gained	Payer's perspective	CUA	Decision tree and Markov model	No AI	Per-test charges
van Leeuwen, K. G. et al.	Tertiary care	ICER per QALY gained	Societal perspective	CUA	Markov model	Standard care	Per-test charges
Mallow, P. J. et al.	Primary care	ICER per QALY gained	Payer's and employer's perspectives	CUA	Markov model	Standard care	Per-test charges
Areia, M. et al.	Outpatient/ Screening	Cost, yearly additional prevention of colorectal cancer cases and related deaths	Societal perspective	CEA	Markov model	Standard care	Per-test charges
de Vos, J. et al.	Tertiary care	ICER per QALY gained	Societal perspective	CUA	Markov model	Standard care	Software licensing
Ericson, O. et al.	Intensive care unit	ICER per QALY gained	Societal and health care system perspectives	CUA	Decision tree and Markov model	Standard care	Per-test charges
Fuller, S. D. et al.	Primary care	ICER per QALY gained	Health care system	CUA	Decision tree and Markov model	No AI	Software licensing/ Per-test charges/ Maintenance fees
Gomez Rossi, J. et al.	Outpatient care	ICER per QALY gained, ICER per tooth-retention year, and diagnostic costs	Payer's perspective	CUA	Markov model	Standard care	Per-test charges

Huang, X. M. et al.	Community-based care	ICER per QALY gained	Societal and health care system perspectives	CUA	Decision tree and Markov model	Standard care	Software licensing/ Per-test charges/ Maintenance fees
Mital, S. and H. V. Nguyen	Preventive Oncology	ICER per QALY gained	Health care system	CUA	Hybrid: decision tree and other	No AI	Software licensing/ Per-test charges
Morrison, S. L. et al.	Tertiary neonatal care	ICER per QALY gained	Health care system	CUA	Decision tree	Standard care	Per-test charges
Ziegelmayer, S. et al.	Tertiary care	ICER per QALY gained	Payer's perspective	CUA	Markov model	Standard care	Per-test charges
Schwendicke, F. et al.	Outpatient dental care	Incremental cost per gained year of tooth retention	Health care system perspective	CEA	Markov model	Standard care	Per-test charges
Barkun, A. N. et al.	Outpatient screening	ICER per QALY gained	Payer's perspective	CUA	Markov model	Standard care	Software licensing
Hassan, C. et al.	Tertiary care	ICER per QALY gained	Payer's perspective	CUA	Markov model	No AI	Software licensing/ Per-test charges/ Maintenance fees
Li, H. et al.	Community-based care	ICER per QALY gained	Health care system	CUA	Markov model	No AI	Software licensing/ Per-test charges/ Maintenance fees
Lin, S. et al.	Community-based outpatient	ICER per QALY gained	Societal perspective	CUA	Markov model	Standard care	Software licensing/ Per-test charges/ Maintenance fees
Liu, H. et al.	Community screening	ICER per QALY gained	Societal perspective	CUA	Markov model	No AI	Per-test charges
Pham, C. T. et al.	Hospital inpatient subacute care	Incremental cost per admission without an injurious fall	Health care system	CEA	Others	Standard care	Maintenance fees
Pickhardt, P. J. et al.	Opportunistic imaging in routine CT scans	ICER per QALY gained	Health care system	CUA	Markov model	No AI	Per-test charges
Shen, M. et al.	Community screening program	ICER per QALY gained	Health care system	CUA	Markov model	Standard care	Software licensing/ Per-test charges/ Maintenance fees
Srisubat, A. et al.	Primary care	ICER per QALY gained	Societal and health care system perspectives	CUA	Hybrid: decision tree and other	No AI	Per-test charges
Chawla, H. et al.	Primary care	ICER per QALY gained	Payer's perspective	CUA	Markov model	Another tool	Per-test charges
Curl, P. K. et al.	Tertiary care	ICER per QALY gained	Societal perspective	CUA	Decision tree and Markov model	No AI	Per-test charges/ Maintenance fees
Ginsberg, G. M. et al.	Tertiary care	ICER per QALY gained	Societal perspective	CUA	Markov model	Standard care	Per-test charges
Hill, H. et al.	Population screening	Incremental net monetary benefit based on QALYs	Payer's perspective	CUA	Markov model	No AI	Not specified
Hu, W. et al.	Primary care	ICER per QALY gained	Health care system	CUA	Markov model	No AI	Software licensing/ Per-test charges/ Maintenance fees
Kongstad, L. P. et al.	National screening program	ICER per QALY gained	Societal and health care system perspectives	CUA	Others	Standard care	Software licensing
Lin, S. et al.	Community	ICER per QALY gained	Societal perspective	CUA	Markov model	Standard care	Software licensing/ Maintenance fees

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Table 2. (continued)

Author	Setting	Primary outcome	Perspective	HEE type	DAM type	Comparator	Type of AI cost
Liu, W. T. et al.	Primary care	ICER per QALY gained	Health care system	CUA	Decision tree and Markov model	No AI	Software licensing/ Per-test charges
Marka, A. W. et al.	Tertiary care	ICER per QALY gained	Payer's perspective	CUA	Decision tree and Markov model	Standard care	Per-test charges
Sun, M. Y. et al.	Tertiary care	Incremental cost per cure	Health care system	CEA	Decision tree	Standard care	Maintenance fees
Tsiachristas, A. et al.	Specialist imaging center	ICER per QALY gained	Health care system	CUA	Decision tree and Markov model	Standard care	Software licensing/ Per-test charges/ Maintenance fees
Wang, Y. et al.	National screening program	ICER per QALY gained	Societal perspective	CUA	Decision tree and Markov model	No AI	Not specified
Wu, X. et al.	Urban and Rural	ICER per QALY gained	Societal perspective	CUA	Markov model	No AI	Maintenance fees
Yonazu, S. et al.	Tertiary endoscopy unit	ICER per QALY gained	Health care system	CUA	Decision tree and Markov model	Standard care	Software licensing/ Per-test charges
Zanghelini, F. et al.	Outpatient rehabilitation	ICER per QALY gained	Health care system	CUA	Decision tree	Standard care	Per-test charges
Zwerwer, L. R. et al.	Tertiary care	ICER per QALY gained	Health care system	CUA	Decision tree and Markov model	Standard care	Software licensing/ Per-test charges/ Maintenance fees
Ahmed, M. et al.	Health system	ICER per QALY gained	Health care system	CUA	Decision tree	Standard care	Software licensing/ Per-test charges/ Maintenance fees
Akune, Y. et al.	National health checkups	ICER per QALY gained	Health care system	CUA	Markov model	No AI	Per-test charges
Du, X. et al.	Tertiary care	ICER per QALY gained	Societal and health care system	CUA	Decision tree	Standard care	Per-test charges
Trujillo, J. C. et al.	Health system	ICER per QALY gained	Health care system	CUA	Decision tree and Markov model	No AI	Software licensing
Huang, F. et al.	Community	Cost per cancer detected; cost per life-year gained	Societal and health care system	CUA	Decision tree and Markov model	No AI	Not specified

Abbreviations: AI, artificial intelligence; CBA, cost-benefit analysis; CCA, cost-consequence analysis; CEA, cost-effectiveness analysis; CMA, cost-minimization analysis; CUA, cost-utility analysis; DALY, disability-adjusted life year; DAM, decision-analytic model; HEE, health economic evaluation; ICER, incremental cost-effectiveness ratio; QALY, quality-adjusted life year; T1D, type 1 diabetics; T2D, type 2 diabetics.

and 2025. Research activity in this area has increased steadily, with a marked rise in publications after 2020. The most frequently evaluated applications involved AI for diabetic retinopathy screening, cancer detection, and intensive care support. These trends highlight growing interest in clinically relevant AI tools that are approaching real-world implementation across a range of healthcare settings.

Compared with the earlier review by Kastrup et al. [12], which examined 27 studies published before early 2023, our synthesis included 52 studies, adding 25 more recent articles. This broader scope allowed us to capture emerging applications and methodological developments. Both reviews consistently identified ophthalmology (particularly diabetic retinopathy), oncology (especially colorectal and lung cancer screening), and cardiovascular diseases (AI-ECG and CT-based screening) as the most common focus areas. At the same time, more recent studies have expanded into additional domains, including nutrition diagnostics, opioid use disorder prediction in orthopedic patients, fall prevention in geriatric care, musculoskeletal pain management, and ICU ventilation support. In terms of study perspective, our findings remain consistent with Kastrup et al., showing that most studies continue to adopt a healthcare system viewpoint, with smaller numbers applying payer perspectives. However, our synthesis also highlights a gradual shift toward societal perspectives, which accounted for one-quarter of the included studies. These evaluations incorporated broader elements such as productivity losses and caregiver burden, reflecting increasing recognition that the value of AI in healthcare extends beyond direct clinical and system-level outcomes.

Across all studies, 98% concluded that AI-based strategies were cost-effective, cost-beneficial, or cost-saving, while one study reported conditional findings depending on modeling assumptions. Although this pattern suggests strong potential for AI to generate economic value, it also raises concerns about publication bias. Negative or inconclusive results may remain unpublished due to commercial pressures to demonstrate value, limited journal interest in non-significant findings, or industry reluctance to disclose unfavorable outcomes. This imbalance can distort the evidence base, overstate the economic promise of AI, and hinder objective policy-making. Addressing this challenge requires greater transparency through preregistration of economic evaluations, mandatory disclosure of funding sources, and journal policies encouraging the publication of negative or neutral results.

A key methodological contribution of our review was the systematic extraction of AI-related costs as a dedicated data element. More than 90% of studies reported explicit cost details, such as annual software licensing fees, per-test or per-image charges, and ongoing maintenance or subscription costs. This level of reporting is important because it increases transparency, supports value-for-money assessments, and informs planning for large-scale implementation. At the same time, we observed substantial variation in how costs were defined and reported. Some studies provided detailed breakdowns, whereas others omitted cost data entirely. Inconsistent reporting undermines comparability across studies and reduces the replicability of economic models. To address this gap, we strongly recommend the adoption of a universal cost-reporting framework that explicitly distinguishes three key components: (1) acquisition or development costs (initial capital investment and software design), (2) implementation or integration costs (training, IT infrastructure, and workflow adaptation), and (3) recurring or maintenance costs (licensing, updates, and technical support). Such categorization would promote consistency and improve comparability across AI evaluations conducted in different clinical and policy contexts [34,35].

This review also provides a structured synthesis of economic evaluations of AI-based healthcare interventions across a wide range of clinical areas and regions. Our study systematically extracted detailed data on evaluation types, decision-analytic models, perspectives, and AI-specific cost elements. This granularity allowed for cross-comparisons and the identification of trends often overlooked in prior work. Several limitations should be considered when interpreting these findings. First, heterogeneity in study designs, clinical settings, AI applications, and economic evaluation methods limited our ability to conduct meta-analysis or generate pooled estimates. Differences in model structures, perspectives, cost definitions, and time horizons mean that direct comparisons across studies should be interpreted with caution. Second, AI-related costs were inconsistently reported. While we extracted detailed cost information when available, many studies lacked transparency in defining and itemizing costs, which hindered comparability and transferability. In particular, the absence of clear separation between development, implementation, and maintenance costs may have led to under- or overestimation of AI's economic value. Third, most included studies relied on decision-analytic modeling rather than real-world economic evaluations. Although modeling is useful for exploring long-term outcomes, these analyses depend on assumptions that may not hold in practice, especially for AI systems that evolve dynamically and whose performance varies by context and user engagement. Future research should therefore prioritize prospective real-world evaluations, preferably integrated within randomized controlled trials or large-scale implementation studies, to validate model assumptions and more accurately capture real-world costs and outcomes. Finally, our review focused on studies published between 2019 and 2025. Given the rapid pace of AI development, new applications and updated evaluations are likely to emerge quickly, and the evidence base will require ongoing reassessment.

Conclusion

This systematic review shows that AI-based healthcare interventions are increasingly being evaluated for their economic value, with the vast majority of studies reporting cost-effectiveness or cost savings across a wide range of clinical domains. While these findings suggest strong potential for AI to deliver value, they may also reflect publication bias, as negative or inconclusive results are rarely published. Methodological variability and inconsistent cost reporting further limit comparability and generalizability. We recommend that future evaluations adopt a standardized cost framework separating acquisition/development, implementation/integration, and recurring/maintenance costs. Moreover, real-world, prospective studies should be prioritized to validate model-based assumptions and strengthen the evidence base. Enhancing methodological rigor, transparency, and reporting practices will be essential to generate reliable evidence, support reimbursement decisions, and ensure that investments in AI deliver sustainable value to patients and healthcare systems.

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Conflicts of interest

The authors declare that there is no conflict of interest.

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