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TOPICAL REVIEW

The Economic Value and Clinical Impact of Artificial Intelligence in Healthcare: A Scoping Literature Review

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ABSTRACT Artificial Intelligence (AI)-supported healthcare has seen a substantial rise in development in recent years. The health economic impact is a crucial factor in the decision-making process regarding AI adoption. This study aimed to analyze the latest research progress and evidence on the cost-effectiveness and clinical efficiency of healthcare AI software from various perspectives, as well as to identify future opportunities and remaining challenges. A review of global literature was conducted using two key databases, PubMed and Embase, along with other related bibliographic resources. The literature search yielded 1,178 unique articles, of which 31 were included in our analysis. These studies covered a wide variety of clinical use cases and healthcare domains, including disease diagnosis (n=13, 41.9%), risk analysis (n=6, 19.4%), screening or patient triage (n=6, 19.4%), treatment delivery (n=5, 16.1%), and patient engagement or follow-up (n=1, 3.2%). Among the included studies, 24 (77.4%) examined the cost-effectiveness of AI compared to standard human-based practices from the perspectives of patients, healthcare systems, payors, or society. The remaining 7 studies, including 5 clinical trials, concluded that AI can enhance clinical efficiency by shortening labor time or patient journey in the clinic. The findings of this targeted literature review demonstrated that leveraging AI in human decision-making has the potential to improve multilevel health outcomes. However, there is a shortage of prospective health economic studies, particularly long-term evaluations, highlighting the disparity between the rapid progress of AI and its lagging utilization in real-world practices.

INDEX TERMS Artificial intelligence, cost analysis, cost-benefit analysis, cost-effectiveness, health informatics, machine learning, smart healthcare.

I. INTRODUCTION

During the past decade, technological advancements in healthcare have accelerated with increasing emphasis on remote care, digital health, and high-tech dependence [1]. Analytic software based on artificial intelligence (AI) is capable of drawing inferences from large data sets and has influenced how care is personalized and delivered to patients [2], [3], [4]. In today's era of exponential increases in large health data sets and computing power, AI is now growing in a wide variety of healthcare domains, such as medical diagnosis [5], patient monitoring [6], treatment [7], and drug discovery [8]. In many cases, intelligent software has already demonstrated its capability to outperform traditional methods in terms of accuracy and effectiveness [9]. Consequently, AI carries potential in improving certain patient outcomes and cost savings for healthcare providers and payors [10], [11], [12], [13]. For instance, risk stratification algorithms were shown to reduce misdiagnosis, and unnecessary treatments and medications, saving associated costs for providers and payors [14]. AI has also been developed to solve costly back-office inefficiencies by streamlining administrative workflows and eliminating tedious non-patient-care activities [15]. Additionally,

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TABLE 1. Search keywords, queries, and boolean operators.

Database	Search query	Number of studies
Embase	'('artificial intelligence': ti,ab,kw OR 'ai': ti,ab,kw OR 'machine learning':ti,ab,kw OR 'deep learning':ti,ab,kw OR 'computer aided design/computer aided manufacturing':ti,ab,kw OR 'natural language processing':ti,ab,kw OR 'nlp': ti,ab,kw) AND ('health eff*':ti,ab,kw OR 'economic aspect':ti,ab,kw OR cost:ti,ab,kw OR budget:ti,ab,kw OR revenue:ti,ab,kw OR productivity:ti,ab,kw OR 'cost benefit analysis':ti,ab,kw OR 'return on investment':ti,ab,kw) AND ('healthcare':ti,ab,kw OR 'health':ti,ab,kw) AND [2016-3000]/py	1,220
PubMed	(("artificial intelligence"[Title/Abstract] OR AI[Title/Abstract] OR "machine learning"[Title/Abstract] OR "deep learning"[Title/Abstract] OR "computer aided"[Title/Abstract] OR CAD[Title/Abstract] OR "natural language processing"[Title/Abstract] OR NLP[Title/Abstract]) AND ("health eff*"[Title/Abstract] OR "econom*"[Title/Abstract] OR cost*[Title/Abstract] OR budget*[Title/Abstract] OR revenue*[Title/Abstract] OR ROI[Title/Abstract] OR efficiency*[Title/Abstract] OR productivit*[Title/Abstract] OR "cost benefit analysis"[MeSH Terms]) AND (health[Title/Abstract] OR healthcare[Title/Abstract]) AND 2016/01/01:3000/12/31[Date - Publication]	751
	Total	1,971

technology adoption is also driven by a paradigm shift the healthcare industry is making from a traditional fee-for-service model to a system of value-based care [16], [17]. As the Centers for Medicare & Medicaid Services (CMS) has instituted many value-based purchasing and bundling programs together with incentive payments, hospitals are encouraged to improve the quality and efficiency of their services [18].

Despite that the medical community is being overwhelmed by reports on the accomplishments of AI applications in laboratory settings, evidence supporting the value AI can and will deliver in the real world is still limited owing to its lagging adoption in clinical practice [2]. The adoption of AI can be hindered by a lack of clear return on investment, making it difficult for healthcare providers to justify the implementation spending [19]. As such, the health economic impact of AI has become a crucial consideration in decision-making [20]. Health economic evaluations (HEEs) play a vital role in helping stakeholders allocate their finite resources optimally by measuring the cost-effectiveness of novel technologies [21], [22]. Importantly, the value of AI applications varies among different stakeholders (e.g., patients, care providers, researchers, and policymakers) [23]. However, the majority of existing literature assessing AI algorithms [2], [9] tends to remain broad and general. Therefore, this study attempted to address this gap by reviewing contemporary studies that compare the financial and efficiency impact of AI applications with standard of care (SoC) or other types of care at various levels, including individual, healthcare system, payor, and the society. Additionally, we sought to explore the challenges and future possibilities of state-of-the-art technologies. To the best of our knowledge, this article is one among very scarcely available reviews that comprehensively examine the impact of healthcare AI from multiple stakeholder perspectives. The findings of this study will provide valuable insights for future research in this promising area and support informed decision-making regarding the adoption and implementation of AI.

II. METHODS

A scoping review was conducted to address the research question: how does the use of AI-based software impact health economics and clinical efficiency? The results were reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) checklist when applicable [24].

A. LITERATURE SEARCH STRATEGY

Although AI applications are currently developing at an accelerated speed, the adoption of AI in clinical practice is still obstructed by the limited published real-world research. Therefore, this scoping literature search focused on studies published within the recent 6 years between January 1, 2016, and August 20, 2022. The studies were extracted from two databases, PubMed and Embase separately using the search keywords and Medical Subject Headings terms combined with Boolean operators detailed in Table 1. Additional articles were also retrieved from the reference lists of the included full-text articles.

B. INCLUSION AND EXCLUSION CRITERIA

After removing duplicate articles, titles and abstracts were screened by W.J. for inclusion eligibility. Articles were included if they focused on: (1) a comprehensive description of an AI functionality; (2) concrete health economic efficiency and/or outcomes evaluation of an AI functionality, which is based on a comparison with contemporary SoC, other types of care, or another AI application within the same healthcare setting; or (3) quantitative clinical outcomes of an AI functionality in at least one healthcare system. Articles were excluded if they were: (1) not specific to AI (e.g., general eHealth or mobile health); (2) not a description of or elaborating on any quantitative cost-effective analysis or health-related outcomes of AI applications; (3) focused on physical AI technology (i.e., robotics) instead of software-based technology; (4) opinion papers, conference abstracts, commentaries, letters to the editor, or editorial types of studies; and (5) not presented in the English language. In total, 89 full-text articles were screened independently by W.J.

C. DATA EXTRACTION

Relevant data of the included articles were extracted independently by W.J. using Microsoft Excel (version 16). A data extraction form was designed and included several general aspects of the publications: author(s), year of publication, title, type of publication, patient population, and country. Specific information extracted with regard to the subject AI included description of AI application, technology features, medical field, and application domain (i.e., disease diagnosis, risk analysis, screening or triage, treatment, patient engagement, or follow-up). Finally, extracted information related to health economics involved study analysis perspectives, intervention, and comparator, clinical or economic outcomes, conclusions, and study limitations.

III. RESULTS

A. SEARCH RESULTS

In total, 1,971 articles were retrieved from the initial search. After removing duplicate articles, 59.8% (1,178/1,971) of titles and abstracts were screened, and 92.4% (1,089/1,178) of the records were excluded based on the exclusion criteria. Out of the remaining 7.6% (89/1,178) eligible for full-text screening, 65.2% (58/89) did not meet the inclusion criteria and were excluded. The detailed database search, screening, and selection process with corresponding inclusion/exclusion criteria are shown in Fig 1. A total of 2.6% (31/1,178) of articles were included in this study and read in full text.

B. GENERAL OVERVIEW OF THE INCLUDED STUDIES AND THE EVALUATED AI TECHNOLOGIES

An overview of the characteristics of the included studies and the AI application domains they investigated is summarized in Table 2. The majority of the studies were published in 2020 or later and originated from various countries/regions. The United States produced the most health economic evaluations, whereas China generated the most prospective studies. Of the 31 included studies, 24 (77.4%) adopted a health economic methodology to assess the economic outcomes of using AI products at different stages of development. These studies covered a wide range of healthcare domains, which were categorized into five different categories based on the function and use-case of AI technology — disease diagnosis, risk analysis, screening or triage, treatment, and patient engagement or follow-up. Each of these application domains was supported by AI in at least one included study. Unsurprisingly, disease diagnosis was the dominant field with a total of 13 (41.9%) of articles investigating the use of AI in feature classification, event detection, and prediction. Additionally, 6 (19.4%) studies evaluated AI in risk analysis, which utilized data analytics to predict and stratify risks of undesirable patient outcomes. Another 6 (19.4%) studies focused on AI in population screening and patient triage, with deep learning (DL)-based image analysis being the primary technology used.

C. HEALTH ECONOMIC OUTCOME ANALYSIS OF AI APPLICATIONS

Among all the included studies, HEEs on the use of AI in healthcare were specifically highlighted in our findings (n=24, 77.4%). Table 3 summarizes the study design details, and health economic evidence based on stakeholder perspectives (i.e., patient, healthcare system, payor, or societal), whose judgment or capability was supported, enhanced, or even replaced by AI. In general, there is considerable heterogeneity in the health economic methodology of the included HEEs. The primary health economic analysis was cost-minimization analysis (CMA), comparing two or more alternative interventions assumed to have an equivalent medical effect, with the cost per case as the outcome (n=9, 37.5%) [20]. Most CMAs adopted a healthcare system/provider perspective (n=5, 55.6%), represented by hospital charges and/or opportunistic costs (e.g., potential savings derived from new diagnostic approaches [25], [26]). The other studies incorporated a payor perspective which was reflected through reimbursement from a government or commercial payor, or a societal perspective which varied among studies — such as costs of healthcare utilization, productivity loss, and value of reimbursement for patient care to represent the interest of society and all other stakeholder groups [2], [27]. However, only one study explicitly elaborated on its definition of analysis perspective [26].

In addition to CMA, other types of HEEs were also identified. There were 7 (29.2%) cost-effectiveness analyses (CEA), which aimed to compare the relative costs and health outcomes of different interventions to determine the most cost-effective option [11], [12], [28], [29], [30], [31], [32]. Three studies (12.5%) conducted cost-utility analyses (CUA) assessing the relative cost and outcomes which consider both mortality and morbidity (e.g., quality-adjusted life-years (QALYs) and disability-adjusted life-years (DALYs)) [13], [33], [34]. Two studies (8.3%) performed budget-impact

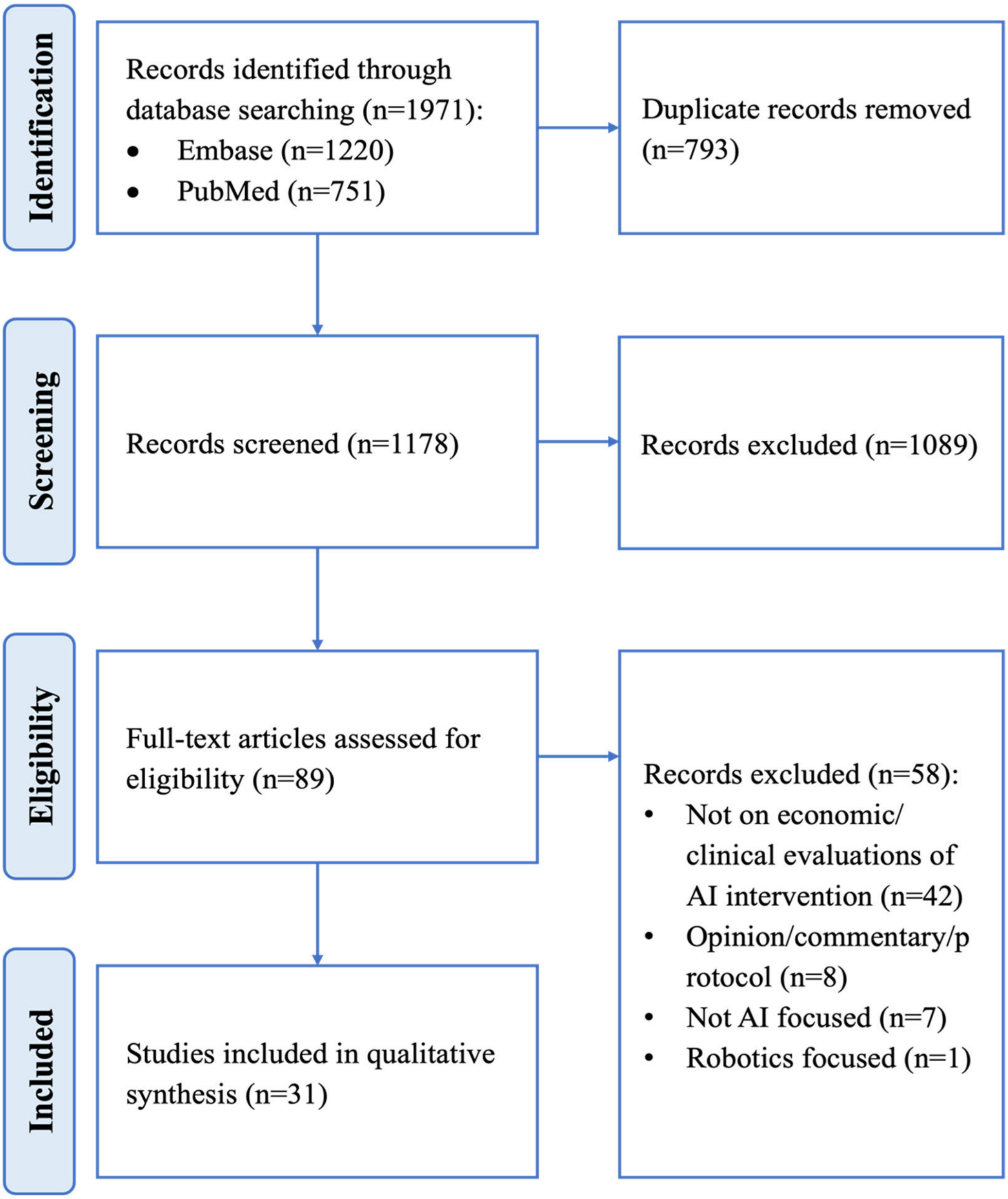

FIGURE 1. PRISMA-ScR (Preferred Reporting Item for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) flow diagram describing study selection and reasons for exclusion during full-text screening.

analyses (BIA), which examined the financial impact of adopting a new intervention within a healthcare system or organization [35], [36]. Finally, one study (4.2%) conducted a cost-consequence analysis (CCA), which evaluated multiple outcomes of interest and costs associated with different interventions [37].

Apart from the conventional HEEs, this review also identified a randomized clinical trial (RCT) and a chart review that evaluated the cost-saving potential of AI interventions [19], [38]. While these studies did not employ standard health economic analysis methods, their focus on the financial implications of AI closely aligned with the goal of HEEs – to assess the value proposition of AI in healthcare. Their inclusion has provided a more comprehensive view of the existing evidence.

D. ECONOMIC VALUE FOR HEALTHCARE SYSTEMS

In all, 58.3% (14/24) of studies investigated whether AI algorithms can outperform traditional clinical practice in terms of healthcare service delivery [11], [12], [13], [14], [19], [25], [26], [29], [32], [36], [37], [39], as well as population-based risk prediction and screening [30], [40]. These studies found that AI could achieve positive financial impacts on service delivery by enhancing disease screening efficiency [14], [25], [29], enabling earlier diagnosis and intervention through risk prediction-enabled [26], [32], [36], [39], reducing healthcare

TABLE 2. Summary of study characteristics (N=31).

Study Characteristics	Value, n (%)
Publication year	
2021	11 (35.5)
2022	9 (29.0)
2020	8 (25.8)
2019	3 (9.7)
2018	1 (3.2)
Country*	
United States	11 (35.5)
China	5 (16.1)
United Kingdom	4 (12.9)
Sweden	1 (3.2)
India	1 (3.2)
Netherlands	1 (3.2)
Spain	1 (3.2)
Singapore	1 (3.2)
Canada	1 (3.2)
Malawi	1 (3.2)
Germany	1 (3.2)
United States, Germany, Brazil	1 (3.2)
Japan, United States, United Kingdom, Norway	1 (3.2)
Study design	
Retrospective observational	22 (71.0)
Clinical trial	5 (16.1)
Prospective	4 (12.9)
Artificial intelligence application domain in healthcare	
Disease diagnosis	13 (41.9)
Risk analysis	6 (19.4)
Screening or triage	6 (19.4)
Treatment	5 (16.1)
Patient engagement or follow-up	1 (3.2)

resource utilization [37], as well as preventing prescription errors and adverse events [11], [19]. Whereas the focus of AI in service delivery is still on the detection, characterization, and prediction of a certain condition, there is also an emerging trend of using AI in actual treatment planning and delivery. For instance, a machine learning (ML)-based personalized psychology treatment recommendation system, as evaluated in an RCT, showed improved patient outcomes compared to usual care, yet at a modest additional cost (£139.83 versus £104.5 per patient in usual care) because more patients accessed treatments [12]. Another AI algorithm designed to decide the antibiotic use for sepsis and lower respiratory tract infections patients was expected to save $25,611 (49% reduction from SoC) for sepsis and $3,630 (23% reduction) for lower respiratory tract infections (LRTI), per patient in a CEA [11].

The potential of AI algorithms to efficiently improve epidemic detection and surveillance has been shown in 3 (12.5%) studies through precise risk stratification [13], [30], [40]. They involved use cases in population-based screening of atrial fibrillation [13], human immunodeficiency virus infection and tuberculosis [30], and glaucoma management [40]. The clinical superiority of AI-based screening over current standard approaches (e.g., opportunistic or health worker-directed screening) was proved in all three studies, in terms of reducing screening volume, undiagnosed or untreated cases, and progression risks [13], [30], [40]. One UK study demonstrated the cost-effectiveness of AI screening strategy versus standard strategies at an incremental cost-effectiveness ratio (ICER) threshold of £20,000 per QALY-gained, with ICERs of £4,847 and £5,544, respectively, despite the increased treatment costs due to longer life expectancy of participants [13]. However, AI algorithms were not found to be cost-effective in the other two studies due to excessive implementation and treatment costs, which may take a larger number of participants or a longer study/modeling period to offset [30], [40].

E. ECONOMIC VALUE FOR PRIVATE AND PUBLIC PAYORS

5 of the 24 studies, (20.8%) highlighted the health economic impact of AI from a payor's perspective [10], [28], [31], [35], [41]. Among them, 4 (80%) studies supported the cost-saving potential of AI algorithms over the current standard practice based on modeling national health

TABLE 3. Economic outcomes of using artificial intelligence (AI) in healthcare from health economic evaluations (N=24).

First Author	Study Design and HEE Type	HEE Method	Real-World AI Implementation[1]	Intervention	Comparator	Perspective	Outcome	Conclusion	Supporting Favorable Economic Outcomes[2]
Boutilier et al	Retrospective CMA	Not model-based	No	Random forest-based risk stratification algorithm for diabetes and hypertension	Developed risk scores from U.S. and U.K.	Health care system	Annual national savings $1.19 billion for diabetes and US$960 million for hypertension by reducing the false negative screenings.	The ML model outperformed the US and UK risk scores.	Yes
Brisimi et al	Retrospective CMA	Not model-based	No	AI methods for classification of diabetes-associated hospitalization risk	Not specified	Health care system	Annual national savings US$1 billion as 17% of hospitalizations can be averted.	The predictive model offers high accuracy and cost-saving potential.	Yes
Datar et al	Retrospective BIA	Budget-impact model	Yes	AI predictive test for diabetic kidney disease progression	SoC (without AI algorithm)	Payor	5-year savings for 100,000 patients were $1.052 billion, attributed mostly to slowed disease progression.	AI-based early identification and intervention is preferred.	Yes
Delgadillo et al	Prospective RCT and CEA	Logistic regression models	Yes	Prognosis ML-based personalized psychology treatment recommendations	Stepped care (patients seeking psychological treatment from guided self-help)	Health care system	AI-instructed care was associated with additional cost per patient (£104.5 vs. $139.83 in stepped care) because more patients accessed high-intensity treatments. The probability of it being cost-effective was 50% if the WTP threshold is greater than £1,320 per additional case of reliable improvement.	AI-instructed care is more costly but more effective.	Mixed
de Vos et al	Retrospective CUA	Markov model	No	AI prediction model for risk of readmission and mortality	SoC (without AI algorithm)	Societal	ICER was €18,507/QALY; The likelihood that AI will be cost-effective was 71% at a WTP threshold of €30 000/QALY driven by reduced ICU length of stay.	Predictive model remained cost-effective over standard care.	Yes
Ericson et al	Retrospective CEA	Decision tree	Yes	AI prediction algorithm for sepsis	Standard diagnosis by physical examination and laboratory data	Health care system	Cost saving was €1,009/ICU patient and aggregated yearly saving for the healthcare system was €2,798,915. Additionally, the algorithm can detect sepsis 3 hours than current practice, potentially resulting in 356 lives saved per year.	Predictive model has cost- and life-saving impact over SoC.	Yes
Fuller et al	Retrospective CEA	Decision tree	Yes	Automated retinal image analysis system for diabetic retinopathy prescreening	SoC (without AI prescreening)	Payor	At 5 years, AI screening showed similar utility as the SoC but reduced costs by 23.3% with $258,721.8 ICUR.	Primary care-based AI prescreening is more cost-effective than SoC.	Yes
Hill et al	Retrospective CUA	Decision tree and Markov model	No	ML predictive algorithm for AFib risk	Traditional methods (systematic and opportunistic screening)	Health care system	In base case where the algorithm had a 50% prediction sensitivity, its cost-effectiveness vs. systematic and opportunistic screening strategies was demonstrated, at an ICER threshold of £20,000 per QALY-gained, with ICERs of £4,847 and £5,544, respectively.	AI risk prediction has the potential to enhance the cost-effectiveness of AFib screening.	Yes
Irvin et al	Retrospective CMA	Decision tree	No	Gradient boosting-based risk prediction and adjustment model for plan payments	Linear regression model for payment adjustment	Payor	AI model reduced misestimation of cost by $3.5MM/10,000 members.	AI outperformed current models.	Yes
Kacew et al	Retrospective CMA	Decision tree	No	Diagnostic algorithm for inferring genetic features for colorectal cancer	SoC (next generation sequencing)	Health care system	AI resulted in shorter time to treatment (<1d vs. 12d for SoC) and $400MM (12.9%) annual savings for new colorectal cancer in the U.S.	AI can reduce both time to treatment and costs compared to SoC alone.	Yes
Lewis et al	Retrospective CCA	Not model-based	No	DL risk stratification for heart failure outcomes	Traditional logistic regression	Health care system	Cost prevention for top 1% of patients was 30.1% (vs. 15% in traditional model); Cost prevention for top 5% patients was 30% (vs.15.6% in traditional model).	DL methods had superior predictive performance over traditional statistical methods.	Yes
Mori et al	Prospective CMA	Not model-based	Yes	Binary AI prediction model for neoplastic colorectal polyps	Resect-all-polyps strategy	Societal	Average colonoscopy cost and the gross annual reimbursement for colonoscopies were reduced by US$149.2MM (18.9%) in Japan, US$12.3MM (6.9%) in England, US$1.1MM (7.6%) in Norway, and US$85.2MM (10.9%) in the U.S.	AI enabled the diagnose-and-leave strategy and reduced costs.	Yes
Rozenblum et al	Retrospective Chart review analysis	Not model-based	Yes	AI prediction application for prescription errors and adverse drug effects	Before the use of AI system	Health care system	Cost of adverse events potentially prevented in an outpatient setting was more than $60 per drug alert and $1.3 million for all patients.	AI system was recommended for use in clinical decision support systems.	Yes

TABLE 3. *(Continued.)* **Economic outcomes of using artificial intelligence (AI) in healthcare from health economic evaluations (N=24).**

Turino et al	Prospective RCT	Not model-based	Yes	ML monitoring system for OSA compliance prediction and treatment recommendation	SoC	Patient	AI significantly increased intervention effectiveness (treatment compliance) without inflicting higher treatment and follow-up costs per patient (SoC: US$105.76 vs. AI: US$112.70, P=.70)	AI-based monitoring increased patient compliance and satisfaction but not costs.	Yes
Van Leeuwen et al	Retrospective CUA	Markov model and decision tree	No	AI-based CT angiography software for stroke diagnosis	SoC (CT evaluated by radiologist or neurologist)	Societal	Incremental cost was −$156, incremental efficacy was +0.0095 QALYs which translated to $244 per patient using a reference value of $25,662 per QALY. Annual national saving was $11MM and QALY gain was 682 ($17.5MM) in the UK.	AI tools demonstrated the potential to improve clinical radiology practices and outcomes.	Yes
Voermans et al	Retrospective CEA	Decision tree	Yes	Decision algorithm to guide antibiotic prescription sepsis and LRTI patients	Before AI implementation	Health care system and societal	Average cost savings of $25,611 (49% reduction from SoC) for sepsis and $3,630 (23% reduction) for LRTI, per patient.	AI decision algorithm intervention was preferred over SoC.	Yes
Xie et al	Retrospective CMA	Decision tree	Yes	DL retinal image analysis system for diabetic retinopathy prescreening	Semi-automated model; Human assessment	Health care system	The semi-automated screening model was the least expensive of the three models (US$62 per patient per year). The annual savings for Singapore health system was $489,000 (20% of current screening cost).	DL systems are an economic assistive tool to screen.	Yes
Gomez Rossi et al	Retrospective CUA	Markov model	No	DL image analysis diagnosis support system	Standard of screening	Health care system	In dermatology, AI showed similar 86.5 QALYs but lower costs of $750 vs control ($759). In dentistry, AI accumulated costs of €320 (vs. €342 in control). In ophthalmology, AI accrued costs of $1321 at 8.4 QALYs, while the control was less expensive ($1260) and associated with similar QALYs.	Current economic benefit of AI as decision support tool should be evaluated on a case-specific basis	Mixed
Szymanski et al	Retrospective BIA	BIM	No	AI risk prediction algorithm for AFib	SoC (routine diagnosis and opportunistic screening), SoC and AI combined use	Health care system	The 3-year NHS budget impact of SoC would be £45.32 million, £3.63 million (difference –92.0%) with AI, and £46.34 million (difference 2.2%) in combined use.	Implementation of a prediction algorithm alongside standard opportunistic screening prevented the most cases and reduced cost	Yes
Kessler et al	Retrospective CMA	Advanced regression models	No	Decision support cloud application for medication and regimen management	Before AI-implementation	Payor	A 19.3% reduction in the total cost of care (P<0.001) yielded a savings of $554 PMPM; medication costs showed a 17.4% reduction (P<0.001) which yielded a savings of $192 PMPM.	AI substantially decreased government health care expenditures	Yes
MacPherson et al	Prospective RCT and CEA	Not model-based	Yes	DCXR screening with CAD	SoC; Oral HIV testing + linkage to care	Health care system	CAD screening reduced undiagnosed or untreated HIV from 10 in the SOC arm to 2 in the HIV screening arm, and 1 in the HIV-TB screening arm. Incremental costs were US$3.58 and US$19.92 per participant screened for HIV and HIV-TB; the probabilities of cost-effectiveness at a US$1,200/ QALY threshold (adjusted based on Malawi GDP) were 83.9% and 0%.	DCXR-CAD with universal HIV and TB screening has potential to improve timeliness and efficiency of diagnosis and treatment	No
Schwendicke et al	Prospective RCT and CEA	Markov model	Yes	AI-based radiographic viewing software for dental caries detecting and classifying	SoC (without AI algorithm)	Payor	AI-supported detection was significantly more sensitive than detection without AI but showed identical effectiveness and nearly identical costs (AI: 330 Euro, no AI: 330 Euro).	Higher accuracy of AI did not lead to higher cost-effectiveness, as more invasive treatment approaches generated costs	Mixed
Xiao et al	Retrospective CMA	Markov model	Yes	DL fundus image analysis system for PACG diagnosis	Without AI-based screening	Health care system	The 5-, 10-, and 15-year accumulated incremental costs of screening vs. no screening were estimated to be $396,362.8, $424,907.9, and $434,903.2, respectively. As a result, the incremental cost per PACG of any stages prevented was $1464.3.	Population screening with AI diagnosis for PACG were able to reduce disease progression risks which could not offset the excessive screening cost.	No
Wolf et al	Retrospective CMA	Decision tree	No	Autonomous point-of-care diabetic retinopathy screening	Clinician-based screening	Patient	ICER of $31 for T1D and $95 for T2D for each additional diabetic retinopathy were identified compared with standard practice.	AI screening is effective and cost-saving for the patient and family	Yes

AFib, atrial fibrillation; BIA, budget-impact analysis; CCA, cost-consequence analysis; CEA, cost-effectiveness analysis; CMA, cost-minimization analysis; CT, computed tomography; CUA, cost-utility analysis; DCXR, digital chest X-ray; DL, deep learning; GDP, gross domestic product; ICER, incremental cost-effectiveness ratio; ICU, intensive care unit; ICUR, incremental cost-utility ratio; LRTI, lower respiratory tract infection; OSA, obstructive sleep apnea; PACG, primary angle-closure glaucoma; PMPM, per member per month; QALY, quality-adjusted life-year; SoC, standard of care; TB, tuberculosis; WTP, willingness-to-pay.

[1] A "Yes" or "No" indicates whether or not an AI product has been implemented/experimented in the real-world practice, regardless of the data collection methods of the study.
[2] A "Yes" or "No" indicates whether or not the study concluded AI was found to be more cost-effective than the comparator. If a study found AI to be equally cost-effective with the comparator, or provided uncertain conclusion therein, it is labeled as "Mixed".

plan, claims, or previous prospective study data [10], [34], [35], [41]. By implementing AI platforms that can identify members at high risk and provide decision support to clinicians in performing interventions on them, costs and utilizations were substantially attenuated [28], [35]. Interestingly, AI algorithms were also utilized to automate plan payment adjustments, reducing payment misestimation [10]. AI-assisted medication and regimen management for government payors yielded a 19.3% reduction in the total cost of care and savings of $554 per member per month [41]. In contrast, one RCT conducted in Germany found that despite the higher accuracy of AI in lesion detection, it led to nearly identical effectiveness or costs with dentist-only assessments as more invasive treatment approaches diminished the possible effectiveness advantages of AI [31]. The same study suggested that the cost-effectiveness of AI could be improved by supporting subsequent patient management and being applied in high-risk populations [31].

F. ECONOMIC VALUE FOR DIFFERENT STAKEHOLDERS IN A SOCIETY

Overall, 3 (12.5%) studies discussed the potential of AI to be cost-effective compared with the SoC from a societal perspective. These studies showed superior performance of AI in terms of improving healthcare outcomes and cost savings across different medical fields and cost components [5], [33], [34]. In a critical care setting, an AI-based decision support tool resulted in more health gains (0.002 incremental QALYs) but slightly incremental costs (€34) (including healthcare costs, informal care costs, and productivity losses) per patient compared with SoC, resulting in an ICER of €18 507 per QALY per patient. Nonetheless, the cost can be compensated for by the reduction in intensive care unit (ICU) stays and fewer readmissions in one year [40]. The cost-effectiveness of this AI-based tool was also assessed through probabilistic sensitivity analysis which showed that when applying a willingness-to-pay (WTP) threshold of €80,000 per QALY (considered the maximum reference value in The Netherlands), the AI tool had a 92% probability of being cost-effective compared with SoC, indicating the potential cost-effectiveness of the tool in real world. Another study assessed the value of AI prediction in radiology by modeling both the short-term healthcare costs and long-term personal social service costs, and showed that AI could potentially help to save $244 per patient and $11 million nationwide each year [34]. While estimated cost savings for the society can be significant, it is equally important to consider the various stakeholders involved to achieve a more balanced assessment of the implication of AI applications. An add-on health economic analysis of a clinical trial showed that using AI prediction in colonoscopy diagnosis was estimated to reduce the exam cost and the gross annual reimbursement by US$149.2 million in Japan, US$12.3 million in England, US$1.1 million in Norway, and US$85.2 million in the United States, respectively [5]. However, healthcare providers may face challenges such as a decline in profits due to reduced reimbursement, which could lead to difficult decisions regarding resource allocation and discourage financial investment in AI technology.

G. ECONOMIC VALUE FOR PATIENTS

Out of the 24 studies, 2 (8.3%) studies evaluated the health economic outcomes of utilizing AI compared with human-based standard practices for patients [38], [42]. One study used decision analysis to model the health economic impact of autonomous AI point-of-care diabetic retinopathy screening in a clinic setting. The findings showed that AI screening detected more cases than clinician screening and was associated with reduced out-of-pocket payments when at least 23% of patients adhered to the AI strategy [42]. Another RCT demonstrated a favorable economic outcome of an intelligent obstructive sleep apnea monitoring system which significantly increased treatment compliance without incurring additional costs for patients compared with usual care (US$112.70 vs. US$105.76, p=0.70) [38].

H. IMPROVED CLINICAL EFFICIENCY OR EFFECTIVENESS BY USING AI

Besides the direct HEEs on the use of AI in healthcare, 7 (22.6%) additional studies measured the impact of AI-supported interventions on clinical efficiency by measuring physician time [43], [44], [45], [46], [47] or the length of hospitalization, which could translate into potential financial and operational benefits for both patients and healthcare providers [48], [49]. Detailed study design information and findings were also summarized, incorporating stakeholder perspectives, as shown in Table 4. Among them, 5 (71.4%) studies have shown that AI software can reduce time spent by providers at multiple stages throughout the care pathway from disease screening [47], diagnosis [43], [45], to intervention [46], and to follow-up [44], compared with manual practice. Three of the five studies evaluated DL-powered image analysis systems which significantly shortened the reading and diagnosis time for clinicians, allowing them to treat more patients [43], [45], [47]. In terms of patient experience, a prospective study and a retrospective clinical trial showed that image-analytic DL systems can reduce the length of stay at the hospital [48] and emergency department [49], leading to accelerated patient turnaround, lower expenses on hospitalization, and most importantly, improved quality of life after timely treatment (e.g., energy level, social function, general health condition as measured by 36-item short form survey [SF-36] scale).

IV. DISCUSSION

Given the potential benefits AI has for the healthcare industry, our work sought to identify and summarize the existing evidence regarding the comparative outcomes that healthcare AI can confer. Through an analysis of the 31 studies we identified, an overall positive answer is revealed to the overarching research question of the economic impact and clinical effectiveness AI applications have on patients, healthcare

TABLE 4. Clinical efficiency outcomes of using artificial intelligence (AI) in healthcare (N=7).

First Author	Study Design	Intervention	Comparator	AI Application Function	Perspective	Outcome	Conclusion
Wang et al	Chart review analysis	DL segmentation algorithm for spontaneous intracerebral hemorrhage volume	Radiologist assessment; ABC/2 scores	Diagnosis	Health care system	AI segmentation saved 25.12 min/scan compared to radiologist assessment ($P<0.001$) and had higher accuracy than ABC/2 sores	AI-based diagnostic system was preferred
Bian et al	Prospective	AI-assisted follow-up system via speech recognition and human voice simulation technology	Manual follow-up	Follow-up	Health care system	The time spent on 100 patients was close to 87.7 seconds in AI-assisted follow-up vs. 9.3 hours in the manual follow-up group	The effectiveness of AI-assisted follow-up was comparable to that of manual follow-up
Liu et al	Prospective	DL-based diseases detection and classification of image analysis	Before the implementation of AI dentist system	Diagnosis	Health care system	The mean diagnosis time was reduced by 37.5% for each patient, leading to an increase of treated patients by 18.4%	AI platform has greatly improved the patient rate and the resource utilization rate at 10 dental clinics
Burns et al	Prospective	AI algorithm for acute illness detection	SoC (without AI algorithm)	Intervention	Health care system	The time required to order investigations ($P=0.049$), contact senior medical staff ($P=0.040$) and senior medical staff intervention ($P=0.045$) was reduced	AI software program can facilitate best clinical practices and reduce staff workloads
Chen et al	Prospective	DL-based echocardiography	Routine echocardiography	Diagnosis	Patient	Average hospitalization cost was significantly lower in the intervention group than SoC group (¥9220 vs. ¥12522)	Echocardiographic detection based on DL algorithm is worthy of further clinical promotion and use
Chien et al	Retrospective clinical trial	NCCT image analytic DL algorithm system	Image interpretation by physicians	Diagnosis	Health care system	For patients with a final diagnosis of ICH, DL system significantly shortened their LOS (560.67min vs. 780.83 min without DL)	AI system accelerated patient flow and improved quality of care
Mayo et al	Retrospective	DL-based, CAD software for mammography image analysis	FDA-approved conventional CAD	Screening	Health care system	A 69% decrease in false positives per image using DL-based CAD as compared to CAD, which could result in a 17% decrease in radiologist reading time per case	AI can decrease false-positive recalls in screening mammography, generating potential economic benefits

CAD, computer-aided design; DL, deep learning; ICH, intra-cranial hemorrhage; LOS, length of stay; NCCT, non-contrast head computed tomography; SoC, standard of care.

systems, payors, and society. Among the 31 studies analyzed, 24 examined the cost-saving potential of AI compared to current standard practices, focusing on potential direct cost savings or efficiency improvements for corresponding stakeholders. Remarkably, 19 of these studies demonstrated favorable findings for the economic benefits of using AI, whereas 3 studies reported either no difference or inconclusive results [12], [29], [31], and 2 studies yielded results that did not substantiate its cost-effectiveness [30], [40], as labeled in Table 3. These variations highlight the need for further research to assess AI's applicability on a case-specific basis and explore strategies to effectively control the incremental cost inflicted by the application of AI. Moreover, we identified 7 additional studies, including 5 clinical trials, compared AI applications with human-based SoC and concluded that AI is more clinically effective by shortening labor time or patient journey in the clinic. The most popular AI technique was neural network-based image analysis systems. We also found that the investigated AI applications have been primarily implemented to provide decision support in disease diagnosis (n=13), followed by risk analysis (n=6), screening or patient triage (n=6), and treatment (n=5).

In the past 10 years, the world has seen significant growth in AI research and development as the number of

AI patents filed in 2021 was more than 21 times higher than in 2015, showing a compound annual growth rate of 76.9% [50]. Although AI adoption is expected to be more widespread, evidence ascribing the cost-effectiveness of AI is still scarce. Considering the tremendous number of English-language publications related to AI development or application in 2021 (over 334,497 globally), 31 articles is a surprisingly limited number [51]. Particularly, many of the 31 included studies adopted a retrospective design projecting future cost based on real-world data, without actually implementing AI in the clinic. Additionally, as previous systematic reviews have reported, the limited number of assessments are often of suboptimal study quality considering the model reliability, and the transparency of their assumptions and analytical methods [2], [21]. Device implementation investment (e.g., device acquisition, training, consumables) was not accounted for in the cost-saving estimates in most studies. This could still allow for payer-providers to determine the savings by subtracting costs from predicted values, but the significance of AI's cost-saving impact would be undermined. Moreover, with the involvement of AI algorithms, healthcare systems and regulation agencies are facing a significant challenge in preserving privacy and security, of which the violation can result in the compromise of patient privacy, erosion of trust in the healthcare system, and have legal and financial repercussions [51]. Although it is hard to monetize the harm of data breaches accurately, failing to account for potential security violations in economic evaluations may lead to an overestimation of the benefits of AI since the possibility of data breaches and exploitation increases day by day as a result of rising demand and dependence on digital technology in this AI age [51]. These observations, combined, point to the need for more qualitatively solid scientific evidence in a real clinical environment, which would require more cooperation between healthcare providers and the AI development community.

This review found that healthcare AI is able to achieve economic advantages for a variety of stakeholders, with a healthcare system's perspective adopted by more than half of the identified HEEs (n=14, 58.3%). This can be partially attributed to the surging healthcare demand that has particularly taken a toll on global healthcare systems since the outbreak of the global coronavirus disease 2019 (COVID-19) pandemic [1]. Novel technology that holds the promise to solve the incapacity to manage sudden and persistent pressures on providers' workload and provisions has thus gained increasing attention from healthcare systems, especially regarding their financial implications. However, the limited evidence of HEEs of AI for other stakeholders (i.e., patients, payors, and society) is insufficient to inform long-term decision-making. Potential challenges and conflicts may arise between different stakeholders as far as the financial implication is concerned. For example, while healthcare systems may benefit from cost savings and increased efficiency with the implementation of AI, payors and society may have different concerns and priorities [52]. Given the rapidly emerging AI applications in the areas of point-of-care diagnostics, remote patient monitoring, reimbursement, and price tiering [53], we encourage future research to include more diverse perspectives in the design and evaluation of state-of-the-art AI products, along with considerations on the unintended consequences and the need for ongoing monitoring.

In addition to the original research, we have identified 19 systematic and scoping reviews carried out in the healthcare AI area. Some reviews focused on the utility and cost-effectiveness of AI technologies in specific clinical domains, such as the cardiovascular disease diagnosis [54], oncology diagnosis and precision medicine [55], [56], [57], anesthesia and perioperative care [58], operating room management [15], ICU management [59], and orthognathic surgery planning [60]. Under these specific clinical contexts, studies indicated that a hybrid model, where AI systems undertake an assistive role alongside human decision-makers, is more effective than relying solely on manual interventions. Furthermore, the joint forces of AI and IoT technologies might allow humans to harvest the economies of scale by not only streamlining clinical processes but also reducing fixed infrastructure costs and overhead expenditures [54]. Another stream of reviews comprehensively characterized existing AI tools in healthcare with differing technology focuses [3], [61], [62], [63], [64], [65], [66]. They provided a fundamental reference to inform the understanding of main AI functionalities and related outcomes. Nevertheless, most studies discussed some substantial problems that have delayed a broad adoption of AI in healthcare, including AI's transparency and interpretability, intrinsic bias against underrepresented persons [56], massive investment and personnel training [62], as well as challenges in overseeing and regulating complex software products [3]. Whether or not reliance on such technologies may exacerbate health inequity is difficult to assess using currently available data in the literature. In this regard, Chew et al conducted a systematic review to describe how AI developers and users perceive these trade-offs and suggested several mitigation strategies, such as enhancing empathy and personification of AI, interconnecting with other devices, and educating the public on AI capabilities [9].

In alignment with previously published review articles on the topic of healthcare AI [2], [66], we found that nearly two-thirds of the identified studies were based in developed economics, of which more than half were from the United States. The United States has held the lead in the number of AI publications (n=11, 35.5%), which is twice as many as China (n=5, 16.1%) or the UK (n=4, 12.9%), the next two countries on the ranking. Corporate investment in AI, from private investment, mergers, and acquisitions, to public offerings, is a key contributor to AI technology development [50]. Our finding is consistent with the fact that the industrialization of healthcare AI is dominated by developed countries, with the United States leading the world in both total private investment and the number of newly funded companies in medicine and healthcare [50]. The disproportionate distribution of study countries in our search indicated that researchers from low- and middle-income economies with limited resources might have a relatively low publication rate. Additionally, low-resource contexts have different patient populations and limited resources available (e.g., low-quality data collection systems and digital infrastructure) than high-resource environments, which will likely result in predictable decreases in the quality of algorithmic recommendations for care, limiting the promise of healthcare AI to democratize superiority [67]. Furthermore, since the AI systems investigated in the included studies were all concentrated on English-language data sets, it is possible for us to miss research published in non-English writing. Hence, we would like to see more studies that cover the real-world influence should AI underperforms on non-English-based data and minority identities.

A. LIMITATIONS

This study has several limitations. First of all, many articles in our review did not implement all the requirements outlined in commonly used checklists for HEEs; thus, they could be methodologically fallible. However, since it is not a requirement for scoping reviews and our main intention was to conduct a broad-spectrum review of contemporary evidence, we did not conduct a formal quality assessment, evaluate the risk of bias across studies, or perform additional analysis to uniform study outcomes beyond the scope of our review [24]. Additionally, this work is subject to limitations that are inherent to literature reviews in general. Since only PubMed and Embase online databases were searched, relevant articles published exclusively by other databases could have been missed. Although academic publications on this subject have been growing faster and faster in recent years, we only focused on studies published within the last 6 years. However, studies qualified for our assessment were concentrated in the last 3 years, which justifies the time frame of our search. Nevertheless, it is possible that relevant articles not written in English, or the latest findings published in the forms of conference abstracts or professional comments were missed. Lastly, as we discussed above, our findings might not be fully applicable to other geographies as the majority of included studies were from the United States or other developed countries/regions.

V. CONCLUSION

This scoping review has provided an overview of the current state of the literature concerning the economic and clinical implications of AI applications for patients, healthcare systems, payors, and society as a whole. AI holds potential within the healthcare industry, surpassing human capacity in terms of care delivery timeliness and completeness and supporting stakeholders in decision-making. These advancements could potentially lead to improvements in multilevel health outcomes. However, the existing body of studies on the cost-saving potential and clinical efficiency of AI, though promising, is limited with lack of empirical evidence and rigorous evaluation methodologies that account for real-world complexities. The journey towards widespread healthcare practices remains complex and evolving, of which the potential biases, information privacy, and ethical considerations should not be underestimated. Although navigating those uncertainties associated with novel technology is challenging for researchers and decision-makers, the potential benefits of AI warrant a responsible and patient-centered approach which could be achieved by continued investments, interdisciplinary collaborations, and meticulous research efforts.

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