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Economic Evaluations of Artificial Intelligence Implementation in Diabetic Retinopathy Screening

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Abstract

Diabetic retinopathy (DR) is a common complication of diabetes that damages retinal blood vessels and can lead to vision impairment. The application of Artificial Intelligence (AI) in DR screening offers a promising alternative to conventional methods. However, further research is crucial to determine the cost-effectiveness of this intervention. This study systematically reviewed economic evaluations of AI interventions in DR screening using data from PubMed and ScienceDirect (2014–2023). Studies in various healthcare settings assessing cost-effectiveness outcomes, such as incremental cost-effectiveness ratio (ICER) and net monetary benefit, were included. The CHEERS (Consolidated Health Economic Evaluation Reporting Standards) checklist was used to assess the reporting quality of included studies. AI intervention can potentially provide accurate diagnoses by performing complex data analysis quickly and consistently. Despite initial higher costs, AI screening often led to higher quality-adjusted life years (QALYs) and improved healthcare resource allocation, particularly in underserved areas. From several perspectives, AI screening is cost-effective compared to manual screening, which has a lower ICER. Seven out of eight articles concluded that using AI for screening is cost-effective. However, challenges in generalizing AI models across diverse populations suggest a need for further validation to prevent diagnostic bias and ensure healthcare equity. Specifically, the hybrid use of manual screening with AI assistance is more cost-effective than the other comparison methods. AI can improve diagnoses like DR through quick data analysis and accuracy, but human guidance is still needed for algorithm development and decision-making. Combining AI with human involvement can lead to more cost-effective interventions.

Keywords: AI interventions; cost-effective; algorithm; diabetes; ICER

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Introduction

The global incidence of diabetes has substantially risen over the past decade. By 2040, it is projected that the number of people affected by Diabetes Mellitus (DM) will rise by 693 million, accounting for around 9.9% of the global population[1]. Diabetes has various causes, including lifestyle and genetic factors, although other potential causes are currently being researched[2]. The condition occurs when insulin fails to convert glucose into energy, resulting in high blood sugar levels that can lead to various diseases such as stroke, liver impairment, and nerve damage[3]. Diabetic retinopathy (DR) is the most dangerous cause of nerve loss, specifically damage to the eye nerve[4].

DR is a health condition that develops from prolonged high blood sugar levels. This condition leads to damage in the tiny blood vessels within the retina and the tissue at the back of the eye, which is critical for transmitting visual data to the brain[5]. DR is a common and severe consequence of diabetes that can result in significant vision loss, including complete blindness, if not adequately addressed[6]. This disorder explicitly impacts the eye's tiny blood vessels, namely the retinal blood vessels. According to estimates from 2020, the global prevalence of DR among adults was around 103 million. The anticipated figure is expected to increase to 160 million by 2045[7].

There are two categories of DR: non-proliferative (NPDR) and proliferative (PDR). NPDR is the first phase of DR, in which the small blood vessels in the retina swell and enlarge, impairing blood flow and causing microbleeds. Symptoms may not be noticeable at this stage, but patients may experience eye discomfort. In the second stage, patients develop PDR. This advanced stage is characterized by damaged retinal blood vessels that can cause abnormal growth in blood vessels. These new blood vessels are often fragile and can lead to severe bleeding into the eyeball, which can obscure vision or cause blindness. Before the onset of blindness, patients may experience early symptoms such as difficulty distinguishing colours, visible spots, and other forms of visual impairment[8]. DR has several risk factors, including patient age, duration of diabetes, genetics, and accompanying conditions such as pregnancy-related diabetes[9]. Early screening for visual impairment is one intervention implemented, although it requires significant resources and time[10,11].

Type 1 (T1DM) and Type 2 Diabetes Mellitus (T2DM) differ in their risk factors, and the progression of DR. T1DM is often associated with an earlier onset of DR, as long-term blood glucose levels are difficult to regulate. Consequently, T1DM patients require stringent glycemic control from an early stage to delay the progression of DR[5,12]. On the other hand, T2DM patients may experience DR as an early complication due to the gradual and often unnoticed onset of diabetes, which allows vascular damage to accumulate before diagnosis[13]. Research suggests that DR in T2DM patients can become more severe due to delays in initiating insulin therapy. Early intervention, especially with regular blood glucose monitoring and management of other risk factors like hypertension and dyslipidemia, is crucial for minimizing DR progression[14]. Moreover, oxidative stress levels, which vary between T1DM and T2DM patients, are a significant contributor to the difference in DR severity across these types[15,16].

In addition, T1DM is characterized by distinct metabolic changes that contribute to the development of microvascular complications, including DR. These changes include elevated levels of specific metabolites, such as amino acids and lipids, which increase oxidative

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stress and inflammation, exacerbating retinal damage[17,18]. In T2DM, however, the metabolic complexity of the disease, often accompanied by coexisting conditions like hypertension and dyslipidemia, requires a more comprehensive approach to DR management. Such co-morbidities independently contribute to the risk of retinal damage, making it essential for T2DM management to address not only hyperglycemia but also these additional risk factors to effectively prevent DR progression[19].

Furthermore, recent studies emphasize the need for individualized treatment strategies for T2DM patients, as certain metabolic biomarkers, like altered amino acid levels, have been linked to DR progression[20]. Dietary interventions, including low-carbohydrate diets, have also shown promise in stabilizing blood sugar and reducing DR risk in T2DM by mitigating insulin resistance and improving lipid profiles[21]. These findings highlight the importance of tailored therapeutic approaches based on the unique metabolic profiles of each diabetes type to optimize outcomes in DR management.

In additional to these developments, AI automation technology is a potential solution that has emerged with the development of state-of-the-art technology[22]. The integration of AI into the healthcare sector has revolutionized numerous areas, including diagnostics, treatment personalization, and predictive analytics[23–25]. For example, AI has been successfully applied in breast cancer screening using mammography, where it aids in detecting early-stage tumors with high accuracy[26]. Similarly, AI-driven systems have been implemented for pulmonary disease detection through chest X-rays and for cardiovascular risk prediction using patient datasets[27,28]. These examples highlight the versatility and potential of AI in improving health outcomes and optimizing resource allocation[25].

Building on these advancements, AI presents a significant opportunity to enhance diabetic retinopathy (DR) screening by automating retinal image analysis and facilitating early detection. However, further research is needed to evaluate AI technology's effectiveness and economic effects for DR screening compared to conventional methods used for years[29]. AI refers to designing an algorithm to solve a problem, including diagnosing DR as one of its embedded learning programs[30]. AI has advantages over humans, including automated processes and a lower error rate. Additionally, AI can process large amounts of information quickly and accurately.

AI-based DR screening shows variable effectiveness depending on DR severity. At the NPDR stage, where microvascular abnormalities like microaneurysms and minor hemorrhages are still isolated, AI algorithms exhibit high sensitivity in detecting these small lesions due to their high-resolution image analysis capabilities[10]. However, in the PDR stages, the detection becomes challenging as complex neovascularization and retinal detachment require more advanced imaging and data processing. AI solutions must be calibrated to recognize intricate pathological features that appear in later stages of DR, which otherwise may lead to misdiagnosis and delay in critical interventions[31,32].

AI models are often optimized on balanced datasets that may lack examples of advanced DR cases from diverse populations, affecting their generalizability in clinical practice[33]. Furthermore, algorithmic performance is influenced by image quality and variability, particularly in regions with limited resources where standard imaging equipment may not be available[34]. To address these issues, recent

research has proposed continuous monitoring and algorithm adjustment to ensure reliable detection across all stages of DR[35,36].

One of the challenges in adopting AI is that the investment costs are pretty expensive, so economic evaluation studies are needed. Several research has examined the economic assessment of using AI for DR screening in high- (HIC), middle- (MIC), and low-income countries (LIC). These studies have shown that AI has the potential to save costs from multiple perspectives. Therefore, this study provides an overview of the possible cost-effectiveness of AI technology screening DR.

Methods

Eligibility Criteria

Our research focused on AI-driven interventions and comprehensive economic evaluations, primarily targeting cost-effectiveness analysis (CEA), cost-utility analysis (CUA), and cost-benefit analysis (CBA) in comparison to manual DR screening methods. The study populations were drawn from HIC, MIC, and LIC. Only CEAs and CUAs were considered suitable for economic evaluation. The results of these evaluations provided metrics such as the ICER and the net monetary benefit.

The identification of expenses and advantages should be consistent with the selected viewpoint, such as the health care perspective, which includes just direct medical costs, or the society perspective, which includes both direct and indirect costs. These techniques can be classified into trial- and model-based economic assessments. A trial-based method involves collecting all pertinent cost and effect data inside a single clinical trial investigation. A model-based technique involves constructing a decision model, such as a decision tree, Markov model, or discrete event simulation, that synthesizes currently available information in a mathematical model. This model may frequently extrapolate findings over extended periods, such as a lifetime. In addition, research that was published in languages other than English was not included. Lastly, the search was confined to full-text articles published between January 2014 and December 2023 to ensure that the studies considered in the research are the most relevant and up-to-date in the use of AI technology for DR screening. Over the last ten years, AI has advanced quickly and has become popular in many industries, including healthcare.

Literature Search and Study Selection

Numerous research journals were chosen according to defined inclusion and exclusion criteria. Initial searches were conducted in the PubMed and ScienceDirect databases over the past decade (2014-2023) using the keywords 'artificial intelligence' OR 'machine learning' AND 'diabetic retinopathy' AND 'economic evaluation'. The inclusion criteria encompass studies that evaluate and present data on the cost-effectiveness of adoption AI aid in diabetes intervention and studies published in English.

Assessment of Reporting Quality

The extracted final articles were evaluated using the Consolidated Health Economic Evaluation Reporting Standard (CHEERS) checklist[37]. The primary objective of the CHEERS checklist is to offer guidance on enhancing the quality of health economic assessment reports[38]. The CHEERS checklist comprises 28 criteria that evaluate various aspects of quality and reporting standards in economic evaluations. This set of standards includes aspects such as the background and aims of the study, the target demographic and specific groups within it, the location and setting of the study, the perspective from which

the study is conducted, the comparators used, the duration of the study period, the rate of discount applied, the type of health outcomes considered, the approach for measuring effectiveness, the methods for measuring and valuing preference-based parameters of the study, the analysis of incremental costs and outcomes, how uncertainty and variability are addressed, the results of the study, its limitations, its applicability to other contexts, the funding source, and any potential conflicts of interest[37]. Each checklist item in every included study was assigned a rating of either '0' or '1'. The quality of qualifying studies was assessed based on four categories: excellent (100% rating), acceptable (76-99% rating), moderate (51-75% rating), or low (<50% rating)[39].

Result and Discussion

Initially, we identified 143 articles from 2 database sources. Following the selection process based on inclusion and exclusion criteria, eight articles fulfilled the requirements for inclusion in the review. The results of the study selection process are summarized in figure 1. The assessment of reporting quality via the CHEERS 2022 checklist yielded an average rating of 80.5%, as detailed in Table 1. Scores ranged from a low of 71.42% to a high of 85.71%. Out of the studies assessed, seven were rated as good quality, while one received a moderate quality rating. Notably, a full 100% of studies failed to adequately address item 18, "Characterizing heterogeneity" (n=8); 75% fell short on item 19, "Characterizing distributional effects" (n=6); 88% did not meet expectations for item 21, "Approach to engagement with patients and others affected by the study" (n=7); 100% were lacking in item 25, "Effect of engagement with patients and others affected by the study" (n=8); and item 28, "conflict of interest" was inadequately reported by 75% of the studies (n=6).

The summary of included articles is provided in Table 2. A study using a payer perspective assessing the cost-effectiveness of standard versus AI-based screening for DR in low-income patients includes adults aged 18 or older indicated that over five years, the Age-Related Eye Disease Risk Assessment (ARIAS) showed excellent efficiency in screening results[40]. One of the study's most compelling findings is the substantial cost reduction achieved by the ARIAS system. It lowered costs by 23.3% compared to expenses associated with standard filtering systems. The ARIAS system was equivalent to standard screening systems in detecting eye problems, but the cost was lower.

The cost-effectiveness of AI is likely a result of reducing inefficient referrals in patients without evidence of DR, improving adherence to follow-up ophthalmic care suggestions in patients with evidence of vision-threatening DR (vtDR) as determined by ARIAS technology, and subsequently reducing events of severe vision loss (SVL) through the detection and treatment of vtDR. The favourable ICUR comparison further underscores this high cost, with an ICUR of $258,722 compared to a willingness-to-pay threshold of $100,000. This high ICUR value indicates that while ARIAS effectively reduces overall costs and provides clinical benefits, the cost per QALY gained is much higher than the accepted threshold of $100,000. Although ARIAS is cost-saving and beneficial, its cost per QALY gained is higher than what is typically acceptable for new health interventions, suggesting that from a strict cost-utility perspective, it might not be considered cost-effective under the current willingness-to-pay threshold.

This study is limited because it only focuses on the cost-effectiveness of screening and

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treatment in the short term. It solely considers the direct costs from the perspective of the payer. It does not consider extra costs to patients, including absences from work or expenses for transportation, which likely made ARIAS more cost-effective.

The second study, conducted in a rural Chinese population, emphasized that AI screening, despite being more expensive, offers equally good health benefits[22]. The population, whose mean starting age was 44 years old, had recently been diagnosed with diabetes but did not have diabetic retinopathy. Compared to no screening, AI and ophthalmologist screening led to increased costs of $180 and $215, respectively. However, the increased cost was justified by increased health benefits, as measured in QALYs[41]. This approach works very well for assessing the quality of treatment, and many people rely on this system to ascertain the quality of the health system by comparing costs and outcomes.

The ICER value of AI screening was $1,108, meaning the health benefits gained will also increase for that amount spent on AI screening. From a societal perspective, considering all direct and indirect costs, AI screening has an ICER value of $10,347 compared to no screening. This value is below China's cost-effective threshold. While not explicitly country-specific, this value is often used as a threshold in cost-effectiveness analysis in various countries, including China, which usually ranges from 1 to 3 times the population's gross domestic product per capita (GDP) in a given year. In other words, from the societal perspective, AI screening is considered an economic measure and promises health benefits that outweigh the additional costs. Studies indicate that AI can improve efficiency in DR screening through its ability to rapidly process high volumes of images with consistent accuracy, supporting faster and more accurate identification of patients who require urgent treatment[10,42].

The same study, conducted in rural China aged 18 years and above from a healthcare perspective, found that AI-based screening costs are more expensive than manual and no screening. However, it has a more significant positive impact on diabetic patients[43]. Compared to no screening, the ICER of AI-based DR screening was $15,595.47 for every QALY. This ICER value is lower than the cost-effectiveness threshold, set at three times the GDP per capita ($30,230.34). Therefore, AI-based DR screening is considered to be cost-effective. The findings of this study indicate that the widespread adoption of AI-driven DR screening methods in rural regions has the potential to be both practical and economically viable.

However, there remain challenges in validating AI for DR screening across diverse populations, which can affect the technology's overall accuracy and acceptance in various clinical settings. AI models often rely on training data from specific demographics, potentially limiting their generalizability when applied to populations with different genetic, environmental, and health profiles. For example, Ting et al. (2021) note that AI models trained predominantly on Western populations may not perform as effectively in Asian or African populations due to variances in retinal pathology and image quality[44]. This limitation has significant implications for healthcare equity, as it suggests that AI algorithms could introduce diagnostic biases if not rigorously validated across multiple population groups[45]. Therefore, achieving population-specific validation is crucial to ensure AI-driven DR screening tools provide reliable and unbiased results globally, supporting equitable access to quality healthcare across regions. Comprehensive

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cross-validation with representative datasets from diverse populations, as suggested by Xie et al. (2020), is necessary to address these concerns and enhance AI performance in DR screening across heterogeneous patient demographics[46].

Another study by Lin et al.[19] was conducted in an urban population. The results explained that for a 65-year-old resident, the total expected cost was $3182 in the AI model and $3265 in the manual assessment model. The life expectancy without blindness was 9.80 years in the AI model and 9.83 years in the manual assessment. Utility, measured as QALYs, was 6,748 QALYs in the AI model and 6,753 QALYs in the manual assessment model.

Based on the calculation, the ICER for the AI-assisted model was $2553 per year without blindness, indicating the additional cost incurred to achieve a year without blindness in the AI model. The ICUR value was $15,216 per QALY, indicating the additional cost incurred for each additional QALY gained using the AI model. The results showed that replacing traditional manual grading-based telemedicine screening with an AI-driven approach led to a cost reduction of $15,216.96 per participant. However, this change also led to a loss of one additional QALY with ICUR= $15,216.96, suggesting that AI-based telemedicine intervension did not appear cost-effective, based on the standards observed in Shanghai in 2020.

A minimum of U.S $22,600 (equivalent to the GDP per capita) should be saved to justify the loss of one more QALY due to the intervention shift. This outcome is due to the study being conducted with data from the Shanghai region, where labour costs for manual intervention were lower than the investment costs for AI-based screening. If labour costs are cheaper in LMICs, AI may not be cost-effective.

Two studies conducted by Srisubat et al. in 2022 with Thailand population and Tufail et al. in London hospital produced encouraging findings. A study by Srisubat et al. showed that deep learning (DL) screening can reduce costs by $2.70, with a similar QALY of about 0.004 and an incremental net monetary benefit of $24.10 in the base case. The outcomes remained consistent in sensitivity analyses, even when the cost per patient increased from $1.00 to $4.00, against a willingness-to-pay (WTP) threshold of $4,997 per Quality-Adjusted Life Year (QALY) gained[29].

A study by Tufail et al. (2016) also revealed that semi-automated models with machine-learning models are more efficient and cost-effective than manual assessment. There are two distinct approaches to using ARIAS: a substitute for first human grading (strategy 1) and a preliminary filter before central human grading (strategy 2). The ICER ranges between $7.14-$18.69 for strategy one and $4.43-$15.36 for strategy[2].

Separate research conducted on children diagnosed with type 1 (T1D) and type 2 diabetes (T2D) found that the percentage of individuals who tested positive for conventional ophthalmology screening conducted by an Eye Care Professional (ECP), was 0.006 for T1D and 0.01 for T2D48. In addition, the percentage of individuals who tested positive for autonomous AI was 0.03 for T1D and 0.04 for T2D. Autonomous AI for screening would lead to a more significant average payment from patients ($8.52 for T1D and $10.85 for T2D) compared to traditional ECP screening ($7.91 for T1D and $8.20 for T2D).

Our findings suggest that point-of-care DR screening with autonomous AI systems for diabetic children and their caregivers is viable and economically efficient, provided that

recommended adherence levels are achieved. However, a significant limitation of this study is its exclusion of downstream costs related to complications. These costs typically occur later in children compared to adults, and previous models of DR screening that consider long-term consequences, the economic impacts of vision loss, and quality-adjusted life-years saved were not evaluated in this study.

Last research conducted by Xie et al. in 2022 showed that the semi-automated screening model was the most economical from the healthcare system perspective[46]. The main ethnic groups represented in the population were Chinese, Malay, and Indian. This model costs around $62 per patient per year, while the utterly automated model costs around $66 per year. On the other hand, the human assessment model costs approximately $77 per year. Adopting the semi-automated strategy will result in potential cost savings of up to $489,000 for Singapore's healthcare system. The results offered a convincing economic case for using DL systems as a DR screening assistance tool, with the semi-automated intervention combining DL with human assessment being identified as the most cost-effective option.

This research represents the inaugural review to assess the economic viability of AI in DR screening programs. The evaluation of report quality across eight articles highlighted a consistent level of documentation. These studies were performed across diverse times and environments, leading to varied findings on cost-effectiveness, influenced by different contextual factors.

Conclusion

The majority of the articles concluded that using AI for screening is cost-effective. Even though AI can improve diagnoses like DR through quick data analysis and accuracy, human guidance is still needed for algorithm development and decision-making. Combining AI with human involvement can lead to more cost-effective interventions.

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Conflict of Interest

None declared

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Table 1. CHEERS Checklist and its Scores per Article.

Item	Section/ item	Fuller, 2020[40]	Huang, 2022[22]	Li, 2023[43]	Lin, 2023[47]	Srisubat, 2022[29]	Tufail, 2017[49]	Wolf, 2020[48]	Xie, 2020[46]	Total Yes
TITLE										
1.	Title	1	1	1	1	1	1	1	1	8
ABSTRACT										
2.	Abstract	1	1	1	1	1	1	1	1	8
INTRODUCTION										
3.	Background and objectives	1	1	1	1	1	1	1	1	8
METHODS										
4.	Health economic analysis plan	1	1	1	1	1	1	1	1	8
5.	Study population	1	1	1	1	1	1	1	1	8
6.	Setting and location	1	1	1	1	1	1	1	1	8
7.	Comparators	1	1	1	1	1	1	1	1	8
8.	Perspective	1	1	1	1	1	1	1	1	8
9.	Time horizon	1	1	0	1	1	0	0	0	4
10.	Discount rate	1	1	1	1	1	0	0	0	5
11.	Selection of outcomes	1	1	1	1	1	1	1	1	8
12.	Measurement of outcomes	1	1	1	1	1	1	1	1	8
13.	Valuation of outcomes	1	1	1	1	1	1	1	1	8
14.	Measurement and valuation of resources and cost	1	1	1	1	1	1	1	1	8
15.	Currency, price date, and conversion	1	1	1	1	1	1	0	1	7
16.	Rationale and description of the model	1	1	1	1	1	1	0	1	7
17.	Analytics and assumptions	1	1	1	1	1	1	1	1	8
18.	Characterizing heterogeneity	0	0	0	0	0	0	0	0	0

19.	Characterizing distributional effects	1	0	1	0	0	0	0	0	2
20.	Characterizing uncertainty	1	1	1	1	1	0	1	1	7
21.	Approach to engagement with patients and others affected by the study	0	0	1	0	0	0	0	0	1
RESULTS										
22.	Study parameters	1	1	1	1	1	1	1	1	8
23.	Summary of main results	1	1	1	1	1	1	1	1	8
24.	Effect of uncertainty	1	1	1	1	1	1	1	1	8
25.	Effect of engagement with patients and others affected by the study	0	0	0	0	0	0	0	0	0
DISCUSSION										
26.	Study findings, limitation, generalizability, and current knowledge	1	1	1	1	1	1	1	1	8
OTHER RELEVANT INFORMATION										
27.	Source of funding	1	1	1	1	0	1	1	1	7
28.	Conflicts of interest	0	0	0	0	0	1	1	0	2
	Overall quality	24	23	24	23	22	21	20	21	
	(%)	85,71	82,14	85,71	82,14	78,57	75,00	71,42	75,00	

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Table 2. Summary of Included Articles

No	Country	Method	Perspective	Intervention	Comparators	Model Comparison	Result	Limitation	Ref
1	United States	CEA	Payer	Automated Retinal Image Analysis System (ARIAS)	Standard screening methods	Markov model	• ARIAS reduced screening costs by 23.3% (ICUR $258,722) compared to standard methods. • ARIAS had a similar utility to conventional screening at five years, giving 4.94 QALYs. • ARIAS increased adherence to eye examination referrals and decreased the incidence of visual loss	• Willingness-to-pay set at $100,000. • Study model analysis over a relatively short timeframe may affect costs or QALYs. • The study concentrated solely on screening for DR, excluding multiple other eye-related comorbidities that low-income individuals are often susceptible to.	Fuller, 2020[40]

2	China	CEA	Health system and societal	AI screening	No screening and ophthalmologist screening	Markov Model	• From a health perspective, AI and ophthalmology screening systems had additional cost differences of $180 and $215, respectively. • AI had a cost-effective rate of $1,107 based on direct and indirect costs. • From a societal perspective, screening using AI had an ICER of $10,347 versus no screening (very affordable). • QALYs of ophthalmologists, AI and no screening were 16.71, 16.76, and 16.59, respectively.	• Transition probabilities and utility values obtained from other countries • Assumed equal compliance in AI and ophthalmologist screening • Did not consider fundus image grading accuracy • Compared ICER with national GDP instead of rural China • It was presumed that all individuals newly diagnosed with diabetes do not possess DR	Huang, 2022[22]

3.	China	CEA	Healthcare	AI-based screening	No screening and ophthalmologist screening.	Markov model	• ICER of AI-based screening was $5,211.31, and ICUR was 0.33. • ICER of ophthalmologist screening was $2,070.19, and ICUR was -0.31. • Compared with no screening, the ICER of AI-based DR screening was $15,595.47 / QALY, which was lower than the threshold for the ICER.	• The study was conducted in a specific region of rural China, and the findings may not be directly applicable to other regions. • Did not consider patient compliance in the AI-based screening group and ophthalmologists to follow DR screening, monitoring assessments and medication. • The study's findings may not fully capture the real-world complexities and variations in clinical practice, patient preferences, and healthcare delivery systems, limiting the external validity of the results.	Li, 2023[43]

4.	China	CEA - CUA	Societal	AI-based screening	Manual grading-based telemedicine screening	Markov Model	• AI model provided a total of 6,748 QALYs, and the manual assessment resulted in 6,753 QALYs. • The ICER for the AI model was $2,553 per year without blindness. The ICUR at $15,217 per QALY suggested the AI model could have been more cost-effective. • Sensitivity analysis showed that introducing AI would increase referral adherence by 7.5%, outweighing the increase in direct care	• Comparison is limited to centralized screening models. • Impact of different screening models on costs and compliance. • A study based on actual data collected from Shanghai may only represent part of China. • Among the highest in China, labour costs in Shanghai could impact cost-effectiveness.	Lin, 2023[47]

5.	Thailand	CEA - CUA	Societal and provider	Deep learning (DL)	Trained human graders (HG).	Decision tree-Markov model	• Both HG and DL were equally effective at 18.53 LY, with HG achieving 12.857 QALYs and DL 12.862. • Compared to H.G., DL had a $3 incremental cost and $24 iNMB, making it the dominant option for society. • From a provider perspective, DL had a higher incremental cost of $67 and an ICER of $16,020 per QALY. • Using DL and H.G., total annual screening costs were $12 and $13, respectively. • From a societal perspective, DL screening was associated with a $3 cost reduction, a QALY of 0.0043, and an ICER of $24 in the base case.	• There are no national statistics available on the rate of follow-through for referrals or on the health utility values for patients with DR. • Variations in clinical states and utility values among different countries. • The utility estimates from the study in Brazil might not accurately represent those in Thailand.	Srisubat, 2022[29]

6.	United Kingdom	CEA	Provider	ARIAS: - EyeArt - Retmarker	Human graders	Decision tree	• EyeArt's sensitivity point is 94.7% for any retinopathy, 93.8% for referable, and 99.6% for proliferative. • The sensitivity point of Retmarker is 73.0% for detecting any retinopathy, 85.0% for detecting referable retinopathy, and 97.9% for detecting proliferative retinopathy. • Two different strategies for using ARIAS: as a replacement for the initial. • Human grading (strategy 1) and filtering before primary grading (strategy 2). • The TotalThe total manual grader (M.G.) cost was $795,165 for all strategies. • Strategy 1: The total cost of EyeArt was $693,345, with ICER at $7. The total cost of Retmarker was $627,914, with ICER at $19. • Strategy 2: The total cost of EyeArt was $675,139, with ICER at $4. The total cost of Retmarker was $658,013, with ICER at $15.	• The cost-effectiveness of ARIAS in developing-country settings has yet to be discovered. • More research is required to determine how sensitive the ARIAS software is to non-DR eye diseases. • ARIAS systems have not yet received approval for use within the NHS DESP framework. • The applicability of ARIAS to U.S. healthcare settings remains to be determined. • Independent validation of ARIAS is needed for global DR screening.	Tufail, 2017[49]

7.	-	CEA	Patient	Autonomous AI	Eye Care Professional (ECP).	Decision tree	• The projected ratio of correctly identified positive cases in conventional ophthalmological screening by ECP was 0.006 for T1D and 0.01 for T2D. Alternatively, the expected ratio of correctly identified positive cases in autonomous AI was 0.03 for T1D and 0.04 for T2D. • Based on a 20% adherence rate, using autonomous AI is projected to lead to higher average payments for patients with T1D ($8.52) and T2D ($10.85) compared to conventional ECP screening ($7.91 for T1D and $8.20 for T2D). • ICER of $31 (T1D) and $95 (T2D). • The ICER for T1D is $31, while for T2D it is $95.	• The assessment did not evaluate the long-term consequences and expenses of vision loss. • Other vision concerns should be considered. • Healthcare and societal costs are not evaluated.	Wolf, 2020[48]

8.	Singapore	CMA	Healthcare	Automated model	Semi-automated screening and human assessment model.	Decision tree	• The semi-automated screening model costs US$62 per patient per year. • The cost for the fully automated model is $66 per patient annually. • The cost of the human assessing model is $77 per patient annually. • Implementing the semi-automated methodology in the Singapore health system is expected to save $489,000.	• The generalizability of the findings to nations with varying rates of screening acceptance and labour costs is still being determined. • Instances of diabetic macular edema present with mild referable diabetic retinopathy were excluded from the study. • The grading model's sensitivity and specificity may be affected by referral bias.	Xie, 2020[46]

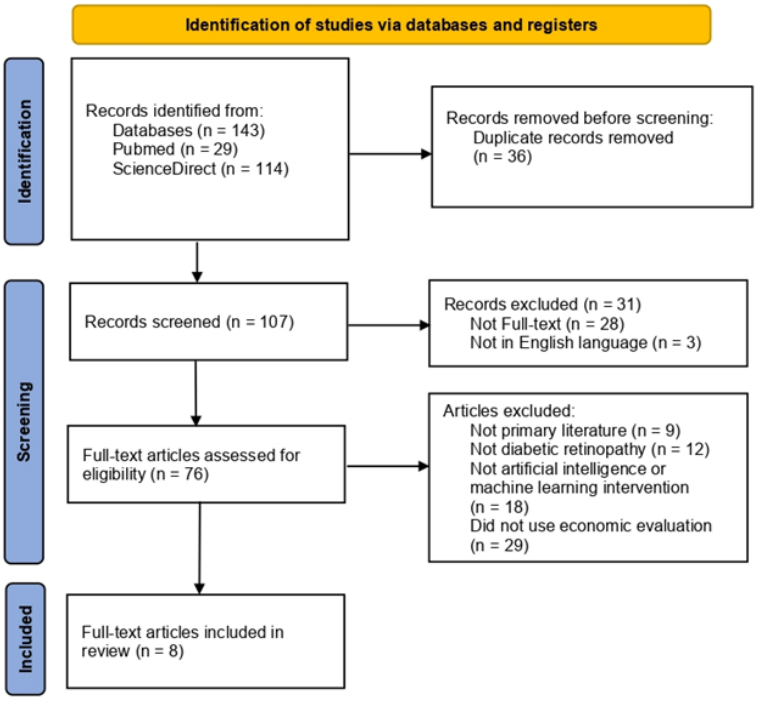

Figure 1. PRISMA Flow chart of the study selection process