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Impact of Artificial Intelligence-Based Visual Screening on the Early Detection of Subclinical Ocular Disorders Among Young Adults

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ABSTRACT: **Background**: Subclinical eye disorders involve early visual system abnormalities which may occur without symptoms or moderate visual impairment. Among the early abnormalities have been observed, with the possibility of affecting young adults, keratoconus, refractive errors, fundus alterations due to myopia, structural anomalies related to glaucoma, and dry eye disease. Traditional eye examinations may not adequately reveal these early abnormalities, especially when access to screening is limited. By employing AI (artificial intelligence) in the visual screening process through automated image analysis, pattern recognition, and clinical decision support, clinicians can potentially detect these abnormalities more reliably . Objective: This review seeks to assess the clinical utility of AI-based visual screening for the early diagnosis of subclinical ocular diseases in young adults. The performance of the diagnosis, screening availability, clinical application, limitations, and future perspectives will be discussed.

Methods: A narrative literature review was performed, with some relevant scientific articles published between 2020-2025. Literature search involved Pub Med, Pub Med Central, Springer Link, Science Direct, and other scientific publication platforms. Search terminologies included artificial intelligence, machine learning, deep learning, ocular screening, ocular subclinical disease, keratoconus, glaucoma, dry eye disease, retinal imaging, young adults. Original articles, systematic review articles, meta-analysis articles, and other relevant clinical review articles were included in the review. Search results were pooled narratively by ocular condition, imaging modality, diagnostic application, and clinical impact. No new patient data and pooled estimates were generated.

Results: The evidence suggests that the use of AI to assist in image interpretation may be helpful in identifying several eye abnormalities, especially those involving retinal photography, optical coherence tomography, corneal tomography, and ocular surface imaging. A 2024 meta-analysis and systematic review of published research regarding AI in dry eye diagnosis reported a pooled diagnostic accuracy of 91.91%, with a mean sensitivity of 89.58% and specificity of 92.62%. Research into the use of AI for keratoconus detection demonstrates the utility of AI for detecting seemingly normal (subclinical) corneal abnormalities that can be difficult to identify with traditional means, as well as retinal AI systems, which have demonstrated strong performance in identifying diabetic retinopathy and other retinal diseases. Of note, the majority of this diagnostic evidence has come from mixed-aged or disease-enriched populations rather than asymptomatic young adults .

Conclusion: Visual screening using AI is a complement to traditional ophthalmic examination and has more potential for diagnosing early structural and functional abnormalities than vision loss, which is commonly observed. Prospective trials are needed to determine the sensitivity and specificity of the predicted threshold for young adults

representative of the general population, in addition to assessing cost-effectiveness, clinical utility and prognostic value.

1. INTRODUCTION

1.1 Background of the Study

Sight is the foundation for learning, ability to work, interaction with others and living a healthy life. The eyeballs at young age should always stay healthy because this stage of life is caused by learning, job, and computer-device usage. Some young adults may see themselves as healthy about their vision, but a lot of eye disorders are without overt symptoms in their early stages, but slowly develop over time (Hashemian et al., 2024; Kazemzadeh, 2025).

Subclinical ocular conditions are early pathological or structural changes, which can be seen through clinical examination or diagnostic testing but may not yet produce symptoms or significant functional disturbance. Examples of these conditions include early keratoconus, mild optic nerve findings, early changes to the retina, mild refractive abnormalities, ocular surface dysfunction (Goodman & Zhu, 2024; Vandevenne et al., 2023).

Detection of these abnormalities is important because early treatment could improve and might even prevent progression, when it can also avoid irretrievable visual impairment. These traditional forms of screening, however, depend on visual acuity testing, subjective complaints and skilled eye care specialists (Hashemian et al., 2024; Kazemzadeh, 2025).

As artificial intelligence (AI) techniques continue to evolve, new opportunities for delivery of ophthalmic screening are being created. AI involves computer algorithms designed to perform tasks normally performed by humans, such as image interpretation, pattern recognition, classification and prediction (Hashemian et al., 2024; Kazemzadeh, 2025).

ML, one of the most important subfields of AI, is aimed at developing computational algorithms that can automatically discover patterns in data. DL, an even more sophisticated form of ML, uses layered neural network algorithms to extract data features from images and other clinical data (Hashemian et al., 2024; Kazemzadeh, 2025).

Within ophthalmology, these methods have been utilized in retinal fundus photography, OCT, corneal tomography, visual fields and ocular surface imaging (Goodman & Zhu, 2024; Vandevenne et al., 2023).

However, there is an essential blind spot in the literature: The accuracy of AI-based screening in seemingly healthy, young adults has not been assessed to the degree it has been in selected clinical populations (Hashemian et al., 2024; Kazemzadeh, 2025).

1.2 Statement of the Problem

Conventional screening programs for visual system may focus on visual acuity measures and complain of symptoms. Although helpful, this might not detect early pathological processes that do not have an initial impact on central visual acuity (Hashemian et al., 2024; Kazemzadeh, 2025). A young adult might have visual acuity that appears within a normal range and yet be suffering from early corneal ectasia, early optic nerve abnormalities, retinal pathologies, or other ocular surface dysfunction (Goodman & Zhu, 2024; Vandevenne et al., 2023). Besides, the availability of specialized eye examinations may be dictated by the specific health system, with limited screening instruments or geographical constraints and increased cost of further investigations likely to contribute to delayed diagnosis of the early onset of disease.

The use of AI-based screening technologies may overcome some of these concerns and pitfalls by providing image analysis and initial risk stratification in an automated manner. Nevertheless, the diagnostic performance of AI screening in young adults and its ability to discriminate normal variants from true abnormalities, along with the potential benefit for real patient outcomes, remain to be elucidated (Hashemian et al., 2024; Kazemzadeh, 2025).

1.3 Rationale of the Review

The review is guided by 4 main arguments, namely: (1) there may be subclinical ocular abnormalities that can go unnoticed when screening is mainly based on symptomatology and visual acuity; (2) the young adult age group is very important when it comes to identifying progressive diseases, particularly keratoconus and abnormality due to myopia; (3) AI-based technologies can offer a screening that is automated, reproducible, and potentially scalable; and (4) the evidence for screening of young adults is currently very limited and should be interpreted critically (Goodman & Zhu, 2024; Vandevenne et al., 2023).

1.4 Purpose of the Review

The aim of this review is to assess the efficacy and effectiveness of visual screening based on artificial intelligence in the early diagnosis of subclinical ocular pathologies in young adults (Hashemian et al., 2024; Kazemzadeh, 2025).

1.5 Specific Objectives

To determine the main subclinical ocular diseases of significance in young adults.

To specify the types of AI technologies and imaging modalities used in ophthalmic screening.

To assess the accuracy of reported diagnostic performance of AI eye screening systems.

To evaluate the use of artificial intelligence aided screening and traditional ophthalmic screening.

To study the advantages and disadvantages of employing AI in the age demographic of young adults.

To contribute to the identification of gaps in the research as well as to propose future clinical applications

1.6 Research Questions

In what ways could a visual screening using artificial intelligence help to detect subclinical eye conditions in young adults?

What eye conditions are most receptive to early detection with the help of AI?

What are the reported diagnostic performance measures of AI in ophthalmic screening?

What benefits does AI offer over standard screening approaches?

What are the barriers that would prevent young adult populations from implementing AI-based screening?

2. LITERATURE REVIEW

2.1 Concept of Artificial Intelligence in Ophthalmology

Artificial intelligence in ophthalmology refers to the application of computer algorithms to interpret clinical images, measurements, and patient data to detect abnormalities and/or assess the risk of a disease (Hashemian et al., 2024; Kazemzadeh, 2025). Machine learning algorithms "learn" from clinical data to identify statistical associations, which can then be used to classify or predict outcomes. Deep learning algorithms, a special case of machine learning that uses neural networks, can automatically discover complex features from images. Computer vision involves interpreting visual information to locate and identify anatomical structures, abnormalities, and patterns.

Convolutional neural networks (CNNs) are particularly relevant as they are able to assess sophisticated image features, such as the appearance of retinal abnormalities, the shape of the optic nerve, and corneal patterns. Nonetheless, the algorithms' performance may be dependent on the quality of images, the dataset, the reference standard, and external validation (Goodman & Zhu, 2024; Vandevenne et al., 2023).

2.2. Young Adults Subclinical Eye Disorders

Structural and functional imaging or other sophisticated ophthalmological tests could reveal subclinical ocular pathology. The most relevant ocular pathologies are subclinical keratoconus, early glaucoma, retinal pathology, dry eye disease, and ametropia, specifically myopia (Goodman & Zhu, 2024; Vandevenne et al., 2023).

2.2.1 Subclinical Keratoconus

In keratoconus (a progressive disease process), the cornea becomes very thin and assumes a cone-shaped protrusion. Corneal shape and biomechanics may be relatively unaffected at the beginning stages of disease but visual acuity is often still within the normal range, making diagnosis more challenging (Goodman & Zhu, 2024; Vandevenne et al., 2023).

AI algorithms can analyze corneal surface curvature, anterior and posterior elevation, pachymetry profile, corneal thickness, biomechanical properties, and Scheimpflug imaging patterns. Maile et al. (2021) provided a review of ML algorithms aimed at identifying subclinical keratoconus. There is also a significant amount of research on the use of AI for keratoconus detection and management including subclinical disease (Goodman & Zhu, 2024; Vandevenne et al., 2023).

2.2.2 Early Glaucomatous Changes

Glaucomatous damage is gradual and includes both optic neuropathy and visual field changes. In early disease, subtle structural alterations may occur in the optic disc, neuroretinal rim, ratio of the cup-to-disc, nerve fiber layer thickness, and ganglion cell complex measurements. Although current studies have shown that AI systems can analyze fundus images and OCT scans and detect abnormal structural features associated with glaucoma, these image-based structural examinations have to be combined with a complete glaucoma workup, which involves intraocular pressure analysis, gonioscopy if necessary, and visual field testing (Coan et al., 2023; Hashemian et al., 2024).

2.2.3 Early Abnormalities of the Retina

There may also be retinal abnormalities that can exist before symptoms of substantial visual loss are experienced by the patient. The retinal conditions of interest include: early diabetic retinopathy in young adults with diabetes mellitus, myopic abnormalities of the macula, abnormalities of the retinal vasculature, abnormalities of the structure of the macula and retinal changes resulting from the optic nerve. AI algorithms have demonstrated the ability to predict suspicious features of the retina using fundus photographs and OCT. While diabetic retinopathy has not yet been recommended for screening in young healthy adults, retinal AI may be useful in young adults with diabetes or other risk factors (Coan et al., 2023; Hashemian et al., 2024).

2.2.4 Dry eye disease and ocular surface problems

Dry eye disease is a complex condition, referring to a collection of symptoms and signs as well as other disorders, including oxidative stress and tear-film instability. Ocular surface abnormalities may be evident in young adults who have high use of digital devices, contact lenses, environmental influences, and additional risk factors. AI application may support evaluation of tear-film breakup pattern, corneal staining, conjunctival abnormalities, tear-film features, and meibomian gland changes. A meta-analysis and systematic review by Heidari et al. (2024) examined applications of AI for dry eye diagnosis (Goodman & Zhu, 2024; Vandevenne et al., 2023).

2.2.5 Refractive errors, Myopia

Myopia matters especially to young adults, because it often first occurs in childhood or adolescence and continues to do so in young adulthood (Hashemian et al., 2024). High myopia has higher risk of retinal and other eye complications. Within existing literature, AI has been explored for prediction of refractive status and detection of myopic-related retinal alteration from fundus images and OCT. Smartphone-based visual testing may be an accessible screening tool but would not sufficiently allow to conclude no ocular abnormality exists (Hashemian et al., 2024; Kazemzadeh, 2025).

2.3 AI Technologies Used in Visual Screening

Machine learning techniques used in ophthalmic image classification include: Convolutional neural networks, which are the most common and can derive visual features from images Support vector machines, which split data into different groups and can be used with a range of different ophthalmic measurements Random forest algorithms, which derive a classification based on combining multiple individual decision trees Multimodal AI, which combines different kinds of clinical data including fundus images, OCT, visual acuity, refractive error, age, and history (Hashemian et al., 2024; Kazemzadeh, 2025).

3. METHODOLOGY

3.1 Study Design

Design This manuscript is a narrative review of the literature. A narrative review was chosen as a mechanism to allow for a critical analysis of current published evidence on the field of AI technologies, ocular imaging, diagnostic performance and may be applicable in screening young adults. This does not constitute a registered systematic review or a meta-analysis. (Hashemian et al., 2024; Kazemzadeh, 2025)

3.2 Search Strategy for Literature

Considering publications (from January 2020 to December 2025) relevant to our subject. Literature search included Pub Med, Pub Med Central, Springer Link, Science Direct, and other publication sources. Search keywords "artificial intelligence AND ophthalmology," "deep learning AND eye screening," "machine learning AND subclinical keratoconus," "AI AND retinal image," "AI AND glaucoma," "AI AND dry eye disease," "artificial intelligence AND myopia," "smartphone-based vision screening," and "young adults AND eye abnormalities." (Goodman & Zhu, 2024; Vandevenne et al., 2023)

3.3 Inclusion Criteria

The sources were considered relevant when the publication date ranged from 2020 to 2025, if they studied applications of AI/machine learning/deep learning, in the domain of ophthalmology, if their focus was on ocular screening/diagnosis/early detection of disease, if they incorporated diagnostic accuracy-related metrics or overall diagnostic performance, had to belong to original research articles, systematic review and meta-analyses, scientific reviews and to be in English language. (Hashemian et al., 2024; Kazemzadeh, 2025)

3.4 Exclusion Criteria

The below articles were also excluded from the main synthesis: articles published before 2020, online sources that did not contain appropriate scientific information, articles that did not measure eye screening or diagnosis, articles that used no diagnostic relationship and only studied treatment, social internet sites, and articles that did not contain appropriate information on the method for use. (Hashemian et al., 2024; Kazemzadeh, 2025)

3.5 Data Extraction

Data was arranged respectively into author and publication date, the disease/ocular condition, AI platform/technology used, imaging modality, main findings, screening in young adult relevance and important limitations. (Hashemian et al., 2024; Kazemzadeh, 2025).

3.6 Data Analysis

Results were qualitatively summarized using a narrative approach and grouped into 5 categories: current AI implementation in the ocular imaging and technology landscape, detection of subclinical ocular abnormalities and diseases, diagnostic accuracy, comparison with traditional screening techniques, and the clinical impact and implementation barriers. No additional quantitative estimates were generated based on studies reviewed in this review. (Hashemian et al., 2024; Kazemzadeh, 2025)

4. RESULTS

4.1 Overview of the Evidence

The literature examined shows that there has been a marked increase of AI in ophthalmology from 2020 to 2025. There was the most amount of published evidence in the areas of retinal imaging, DR, glaucoma, keratoconus and dry eye disease. However, the evidence is of varying quality when considering the different conditions and the technology used. It is important to differentiate the evidence of training performance from optimizing screening in asymptomatic young adults and predominantly relates to the first rather than the second. Further prospective studies may be needed for the latter (Goodman & Zhu, 2024; Vandevenne et al., 2023).

4.2 Major AI Applications in Subclinical Ocular Screening

Table 1. Subclinical ocular disorders and potential AI screening applications

Ocular disorder	Early abnormalities	AI imaging modality	Potential screening value
Subclinical keratoconus	Corneal thinning and irregular elevation	Corneal tomography and topography	Identification of early corneal ectasia
Early glaucoma	Optic disc and nerve fiber abnormalities	Fundus photography and OCT	Detection of suspicious structural changes

Retinal abnormalities	Subtle vascular and macular changes	Fundus photography and OCT	Automated retinal risk classification
Dry eye disease	Tear-film instability and gland abnormalities	Ocular surface imaging	Objective ocular surface assessment
Myopia-related changes	Refractive and retinal structural abnormalities	Fundus photography and OCT	Identification of myopia-related risk
Refractive errors	Abnormal refractive status	Smartphone-based testing and visual assessment	Preliminary identification of refractive problems

Table 1 summarizes the main disorders, early abnormalities, imaging modalities, and potential screening value. (Hashemian et al., 2024; Kazemzadeh, 2025)

4.3 Evidence from Published Studies

Table 2. Selected research publications concerning AI-based ophthalmic screening, 2020–2025

Author and year	Research focus	Main findings / contribution	Relevance
Maile et al. (2021)	Machine learning and subclinical keratoconus	Reviewed algorithms for identifying early corneal abnormalities using clinical and imaging measurements	Direct relevance to subclinical disease
Yang et al. (2022)	AI in dry eye diagnosis and monitoring	Described AI applications in ocular surface assessment	Supports early ocular surface assessment
Chaurasia et al. (2022)	AI in glaucoma screening	Evaluated diagnostic accuracy and factors affecting clinical implementation	Supports optic nerve screening
Coan et al. (2023)	AI-based glaucoma detection	Reviewed automated analysis of optic disc and cup morphology	Supports structural screening
Goodman and Zhu (2024)	AI in keratoconus diagnosis and management	Reviewed original studies, including work on keratoconus and subclinical detection	Strong relevance to early corneal diagnosis
Heidari et al. (2024)	AI in dry eye diagnosis	Systematic review and meta-analysis of diagnostic performance	Supports automated ocular surface assessment
Joseph et al. (2024)	AI-based diabetic retinopathy screening	Evaluated automated screening in real-world settings	Supports targeted retinal screening
Hassan et al. (2024)	AI models for major retinal diseases	Reviewed AI methods for retinal disease detection and grading	Supports automated retinal assessment

Luo et al. (2024)	Smartphone-based subjective refraction	Described a smartphone-based approach for vision screening	Supports accessible preliminary assessment
Muhsin et al. (2025)	Machine learning in keratoconus	Reviewed developments and clinical translation challenges	Supports further AI development

Summary of literature publications on AI-based eye screening (2020–2025), Table 2 The publications listed are for different populations, reference standards, and diagnostic approaches, and therefore should not be considered as directly comparable head-to-head screenings ;

4.4 Diagnostic Accuracy of Screening with AI

The main diagnostic criteria are sensitivity, which is the percentage of all patients with the condition correctly identified, specificity, or the percentage of all patients without the condition correctly diagnosed, accuracy, or the percentage of all correct classifications, and the area under the receiver operating characteristic curve (AUC), an indicator of how well discrimination between the diagnostic groups (Hashemian et al., 2024; Kazemzadeh, 2025).

4.4.1 AI in Dry Eye Disease

Table 3. Reported diagnostic performance of AI in dry eye disease .

Diagnostic measure	Reported result
Number of studies included in meta-analysis	17
Pooled accuracy	91.91%
Mean sensitivity	89.58%
Mean specificity	92.62%
Mean AUC, as reported	94.1% ± 5.14% (0.941 ± 0.0514)

4.4.1 AI Applications in Dry Eye Diagnosis

Heidari et al. (2024) performed a systematic review and meta-analysis on the use of artificial intelligence (AI) on the diagnosis of dry eye disease. The authors found 17 included studies, which resulted in a pooled diagnostic accuracy of 91.91% with an average sensitivity of 89.58% and an average specificity of 92.62%. This suggests AI may have good diagnostic performance, although inconsistency in the methods of capture and definitions of dry eye disease may limit applicability (Heidari et al., 2024; Hashemian et al., 2024).

4.4.2 Diabetic Retinopathy AI

In a publication, Joseph et al. (2024) explored the use of real-world data to study the application of automated AI-based screening for diabetic retinopathy. This paper highlights the importance of evaluating the performance of AI outside of research environments, as real-world settings could affect the success of AI-based screening. Factors that might impact the success of AI-based screening include image quality, patient characteristics, camera systems, disease prevalence, and referrals. While screening for diabetic retinopathy is probably not relevant to all healthy young people, it is relevant to young people with diabetes (Hashemian et al., 2024; Kazemzadeh, 2025).

4.4.3 Keratoconus Detection with AI

Detection of KC is especially important in the young adult population. Maile et al. (2021) reviewed artificial intelligence (AI) approaches for detection of subclinical KC and highlighted that the most successful approach for KC detection involves combining clinical measures and imaging data. Goodman and Zhu (2024) found 93 original articles on AI for KC detection and management, of which 61 articles reported on the detection of KC or subclinical KC. There was considerable heterogeneity

in the reference standards, the population studied and model validation and, thus, it may not be justified to assume all algorithms would perform equally in routine screening of the young adult (Goodman & Zhu, 2024; Vandevenne et al., 2023).

4.4.4 AI in Glaucoma Detection

Coan et al. (2023) performed a review of methods for automated detection of glaucoma with fundus imaging – segmenting the optic disc and optic cup, and classifying suspicious optic nerve abnormalities. Furthermore, Chaurasia et al. (2022) assessed the performance of AI for glaucoma screening and clinical use. These studies suggest that AI can be used as a supplementary method for detection of suspicious optic nerve abnormalities; nevertheless, a clinical correlation is required for a complete diagnosis of glaucoma (Coan et al., 2023; Hashemian et al., 2024).

4.5 Screening with AI Assistance Versus Traditional Approach

Table 4. Comparison of conventional and AI-assisted ocular screening .

Screening characteristic	Conventional screening	AI-assisted screening
Visual acuity	Standard clinical measurement	Can be integrated with digital vision assessment
Image interpretation	Primarily clinician-dependent	Automated algorithm-assisted interpretation
Detection of subtle patterns	Depends on examiner expertise and available equipment	May identify complex image patterns
Screening speed	May require individual specialist assessment	Automated processing can reduce interpretation time
Reproducibility	May vary between examiners	Can improve consistency under standardized conditions
Large-scale screening	May require substantial clinical resources	Potential for scalable image-based assessment
Clinical judgment	Direct professional assessment	Requires professional oversight and confirmation
False-positive results	Possible	Possible, depending on model thresholds
Data protection	Conventional medical record safeguards	Additional digital and algorithmic governance required
Follow-up	Clinician-directed	Can support automated referral and tracking

Conventional screening commonly involves visual acuity testing, refraction, clinical examination, and selected diagnostic investigations. AI-based screening adds automated image interpretation and computational classification. The main potential advantage of AI is not replacement of conventional examination but enhancement of screening capacity and consistency. (Hashemian et al., 2024; Kazemzadeh, 2025)

4.6 Conceptual Framework

Figure 1. Conceptual framework for AI-based visual screening

YOUNG ADULT POPULATION
↓
INITIAL SCREENING

↓
Fundus imaging | OCT imaging | Corneal / ocular surface imaging
↓
AI IMAGE ANALYSIS: feature extraction and pattern recognition
↓
RISK CLASSIFICATION
↓
LOW RISK: routine review / rescreening | SUSPECTED ABNORMALITY: ophthalmologist assessment
↓
Confirmatory testing → Early intervention → Monitoring and follow-up

Source: Author-developed conceptual illustration based on the reviewed literature. (Hashemian et al., 2024; Kazemzadeh, 2025)

Figure 1 presents a conceptual pathway from young adult screening and multimodal imaging through AI analysis, risk classification, professional assessment, confirmatory testing, and early intervention. (Hashemian et al., 2024; Kazemzadeh, 2025)

4.7 Proposed AI-Based Screening Workflow

Figure 2. Suggested clinical workflow for AI-assisted ocular screening.

Registration and consent
↓
Collection of clinical history
↓
Visual acuity and refractive assessment
↓
Standardized ocular imaging
↓
Automated AI interpretation
↓
Risk stratification
↓
LOW RISK: routine review | ABNORMAL / UNCERTAIN: specialist referral
↓
Confirmatory examination → Diagnosis and management → Longitudinal monitoring

Source: Author-developed conceptual illustration based on the reviewed literature. (Hashemian et al., 2024; Kazemzadeh, 2025)

Figure 2 presents a suggested clinical workflow integrating consent, history, visual assessment, standardized imaging, AI interpretation, risk stratification, specialist referral, diagnosis, and longitudinal monitoring. (Hashemian et al., 2024; Kazemzadeh, 2025)

4.8 Potential Impact on Early Detection

Figure 3. Proposed relationship between screening **and clinical outcomes**.

Accessible screening and standardized image acquisition
↓
AI-assisted identification of suspicious abnormalities
↓
Appropriate professional referral and confirmatory diagnosis
↓
Timely monitoring or intervention
↓
Potential reduction in delayed diagnosis and avoidable visual impairment
Note: This is a proposed pathway; improved long-term outcomes require prospective evaluation.

Source: Author-developed conceptual illustration based on the reviewed literature. (Hashemian et al., 2024; Kazemzadeh, 2025)

Possible advantages of AI in visual screening might be earlier detection of small abnormalities, higher consistency in screening, better access to screening for patients, quicker referral pathways, and better long term monitoring. These potential advantages should not be seen as evidence that AI screening has already resulted in a decline in long term visual impairment in young adults (Hashemian et al., 2024; Kazemzadeh, 2025).

5. DISCUSSION

5.1 Overall Explanation of Results

The results indicate that AI-based visual screening may improve detection of subclinical ocular abnormalities. A key advantage of AI is its ability to handle large and complex sets of imaging data in a standardized manner. Some early ocular disorders may result in structural abnormalities before any significant functional deficit becomes apparent. AI systems will likely aid in detecting these abnormalities by identifying patterns that are difficult to evaluate by routine visual screening. Evidence seems most promising in the context of keratoconus, retinal disease, glaucoma, and dry eye disease. However, existing studies do not yet demonstrate that AI screening is more effective than a complete ophthalmic exam for all groups of young adults (Goodman & Zhu, 2024; Vandevenne et al., 2023).

5.2Need for diagnosing keratoconus in its early stages

The significance of the keratoconus is highlighted by the fact that it frequently does not manifest itself until adolescence or young age. An early diagnosis is important as the progressive corneal ectasia causes irregular astigmatism, poor quality of vision and with severe ectasia, eye disability. The use of the AI algorithm could make it easier to combine the individual corneal measurements for an algorithm to detect early signs of ectasia. It is likely that AI corneal tomography will be a vital part of screening for disorders before refractive surgery and if the change in test is abnormal results of the algorithm should be supported with other ways of testing (Goodman & Zhu, 2024; Vandevenne et al., 2023).

5.3 Importance of Retinal and Optic Nerve Screening

Retinal and optic nerve abnormalities may remain asymptomatic during early stages. Fundus photography and OCT provide anatomical information that can be evaluated using AI. Potential applications for young adults include targeted assessment of

individuals with diabetes, high myopia, family history of glaucoma, or suspicious optic nerve findings. The relatively low prevalence of some diseases in otherwise healthy young adults may affect the positive predictive value of screening systems. (Coan et al., 2023; Hashemian et al., 2024)

5.4 AI and Ocular Surface Screening

Dry eye disease is highly relevant to young adults due to its association with climate, contact lens wear, and excessive digital-device usage. It is suggested that AI could aid objective assessment of tear-film parameters and ocular surface images. This meta analysis by Heidari et al (2024) offers encouraging data on the diagnostic performance of AI; but as a disease that involves the presence of signs and symptoms, image analysis should be used in conjunction with valid questionnaires of symptoms and clinical assessments. (Heidari et al., 2024; Hashemian et al., 2024)

5.5 Potential Benefits in University and Community Settings

Of all ages, most young people tend to be concentrated at educational institutions and workplaces which can make these attractive locations for the delivery of preventative eye-health initiatives. AI screening could augment offerings by university health centres, occupational health clinics, community-based ophthalmic campaigns, general practitioner clinics and mobile eye-screening programs. There can be a protocol developed that is standardized on acuity tests, basic refraction, retinal imaging when required and targeted additional imaging. AI could be used to assist with decision-making to identify those in need of a referral for further tests. (Hashemian et al., 2024; Kazemzadeh, 2025)

5.6 AI versus ordinary screening

Conventional screening processes give direct clinical insights and allow for evaluations in the setting of presenting complaints and past records. AI, on the other hand, gives off automated image analysis and possibly improved reliability for specific diagnostic tasks. These methods will probably be complementary. An ideal system may be a hybrid pathway where AI flags suspicious results, which healthcare professionals then validate or dismiss in the course of an examination (Hashemian et al., 2024; Kazemzadeh, 2025).

5.7 Diagnostic accuracy and clinical impact

Screening requires high sensitivity as false negative results could lead to missed detection. Specificity is also a key parameter in screening because false positive can cause unnecessary referrals, false anxiety, further investigations and costs. An algorithm is ideally judged by the clinical application and not by accuracy. In addition, metrics of performance based on a specific research dataset need not necessarily apply to a broad population, devices or a healthcare system. (Hashemian et al., 2024; Kazemzadeh, 2025)

5.8 Implications for Preventive Ophthalmic Care

AI has the potential to lead to the evolution of the managing of disease in preventative ophthalmology from a predominantly symptom-based approach into a well-organized risk-based system. The aim should not only be to detect more abnormal images but to optimize diagnosis, referral, and monitoring and visual health (Hashemian et al., 2024; Kazemzadeh, 2025)

6. LIMITATIONS AND CHALLENGES

6.1. Young Adult-Specific Evidence is Limited

One of the major weaknesses in this area is the available number of prospective studies conducted solely in asymptomatic young adult individuals. Some studies apply to heterogeneous populations of varying ages, or special selected patients who have already been diagnosed. Consequently, the diagnostic accuracy described can be lower or higher than observed in healthy, university students or employed adults.

6.2 Dataset Bias

The training data of the AI models have been a source of concern. If the training data lacks enough identification of differing ethnicity, age, imaging modality, and clinical setting, the model will probable underperform when deploying in a new population.

6.3 Reporting False-Positive and False-Negative Results

The resulting false-positive results could result in more unwarranted referrals and testing. On the other hand, false-negative results could cause unwarranted reassurance and delay diagnosis. As a result, the findings of artificial intelligence should be interpreted in the context of a pathway of clinical referral that is well-defined (Hashemian et al., 2024; Kazemzadeh, 2025).

6.4 Image Quality

Substandard image quality could negatively impact on accuracy of diagnosis. Factors influencing this could be poor illumination, eye movement, fixation loss, media opacities, acquisition technique, and differences between devices among others. Quality control procedures are therefore crucial (Hashemian et al., 2024; Kazemzadeh, 2025).

6.5 Cost and Infrastructure

The costs of the added technology such as sophisticated imaging systems and AI software can also be substantial. In addition to the technology, healthcare facilities may also need to invest in skilled staffing, technology support, secure storage of data and internet or computer access (Hashemian et al., 2024; Kazemzadeh, 2025).

6.6 ethical and legal considerations

Screening with artificial intelligence involves the collection of potentially sensitive health information. Key issues include patient consent, data security and storage, transparency of algorithms, responsibility for diagnostic errors, and appropriate levels of professional supervision (Hashemian et al., 2024; Kazemzadeh, 2025).

6.7 Lack of Longitudinal Outcome Evidence

Higher diagnostic accuracy does not equate to better patient outcomes. More research is needed to evaluate if artificial intelligence screening actually results in a decline of progression of disease, improvement in visual function, or a preservation of long-term visual impairment (Hashemian et al., 2024; Kazemzadeh, 2025).

7. RECOMMENDATIONS

- Based on the evidence reviewed, the following recommendations are proposed:
- Screening using artificial intelligence should be used as a surrogate, not a replacement for a comprehensive ophthalmic examination.
- Individuals with risk factors for keratoconus, glaucoma, high myopia, diabetes, or ocular surface disease should have screening.
- UoH healthcare services to explore. Implementation of structured visual screening programs using technological tools for digital assessment.
- A prospective study is needed to determine the diagnostic accuracy of artificial intelligence among asymptomatic young adults aged 18 to 35 years.
- The algorithms used in artificial intelligence should be tested on other populations and different systems.
- G. screening systems should use standardized measures of image quality. Provisional and equivocal results yielded by artificial intelligence ought to be referrals to experts.
- Healthcare organizations must establish policies on patient consent, confidentiality and data.
- Future research is recommended to assess the cost-effectiveness and long-term clinical outcomes of AI use.
- For research, a good focus may be the development of multi-modality AI models to analyze data of the retina, cornea, eye surface, and clinical data, as appropriate.

8. PROPOSED FUTURE RESEARCH FRAMEWORK

8.1 Suggested Study Design

Table 5. Proposed framework for future primary research

Component	Proposed approach
Study design	Prospective diagnostic accuracy study
Target population	Young adults aged 18–35 years
Study setting	University clinics and community eye-care centers
Sampling	Consecutive or stratified recruitment
Screening methods	Visual acuity, refraction, fundus photography, and indicated OCT or corneal tomography
AI assessment	Validated AI algorithms appropriate to each imaging modality
Reference standard	Independent comprehensive ophthalmic assessment
Primary outcome	Sensitivity and specificity for prespecified ocular abnormalities
Secondary outcomes	AUC, referral rate, PPV, NPV, and screening time
Statistical analysis	Diagnostic accuracy analysis with 95% confidence intervals
Ethical considerations	Informed consent, confidentiality, and professional referral

A prospective observational trial may be carried out to examine the real effects of AI-based visual screening of young adults. A suggested protocol is summarized in Table 5. (Hashemian et al., 2024; Kazemzadeh, 2025)

8.2 Suggested Study Hypotheses

Nil hypothesis (H0): AI-Assisted Visual Screening does not increase the accuracy of diagnosis of young adult subclinical ocular abnormalities. As compared to standard screening method alone. (Hashemian et al., 2024; Kazemzadeh, 2025)

H1: The AI-assisted visual screening program is associated with more detection of subclinical ocular anomalies in young adult patients than visual screening alone. (Hashemian et al., 2024; Kazemzadeh, 2025). These theories need to be tested with new, prospective studies rather than suggested in the literature. (Hashemian et al., 2024; Kazemzadeh, 2025)

9. CONCLUSION

Screening for the early detection of ophthalmic diseases is an area of emerging interest with AI. The references state that AI is capable of analyzing ocular disease images, such as retinal images, OCT images, corneal tomography, and ocular surface images and recognizing patterns that may point to certain disorders. The most significant to young adults could relate to identifying subclinical keratoconus or a thin cornea, myopia-associated structural retinal defects, abnormal optic nerve head, or ocular surface disease. Recent systematic review and diagnostic studies indicate they are performing well on some specific ophthalmic applications. It is especially encouraging in keratoconus and dry eye disease that we know AI can help with identifying abnormalities that are difficult for humans to detect on traditional examination alone. Yet, there is a difference between the diagnostic accuracy within selected research populations and effectiveness in routine screening of asymptomatic young adults. Currently, AI should be regarded as an adjunct screening modality, as a tool to aide professional eye health assessment. Additional prospective research is needed to determine the diagnostic performance, clinical value, cost-effectiveness and potential to improve visual prognosis in young adults in the future. In the end, incorporating validated AI solutions into systematic preventive eye-care management could potentially increase the chance of early detection and appropriate treatment of subclinical eye diseases.

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